

Panel Data and Multilevel Models for Categorical Outcomes: AAPs, AMEs and APRs for Multilevel Models

Richard Williams, University of Notre Dame, <https://academicweb.nd.edu/~rwilliam/>
Institute for Political Methodology, Taiwan, July 17 & 18, 2018

Results from logistic regression and many other methods can often be hard to interpret. For example, what does a coefficient of .2 for female (coded 0 = male, 1 = female) mean? Does it mean females are a little more likely to experience the event, a lot more likely, or what? As with regular logistic regression, adjusted predictions and marginal effects can help with the interpretation of multilevel random effects models. Margins with Fixed effects models are not so straightforward though, and should be approached with caution. For a discussion, see

<http://www.statalist.org/forums/forum/general-stata-discussion/general/1304704-cannot-estimate-marginal-effect-after-xtlogit>

Example. Consider a modified version of our earlier poverty example. This time, we will include an interaction between black and hours. This allows for the possibility that Black people benefit more (or less) than do White people for each hour worked.

```
. melogit pov i.mother i.spouse i.school hours i.year i.black i.black#c.hours age || id:, nolog
```

```
Mixed-effects logistic regression      Number of obs      =      5,755
Group variable:                        id                    Number of groups   =      1,151

                                   Obs per group:
                                   min =           5
                                   avg  =          5.0
                                   max  =           5

Integration method: mvaghermite        Integration pts.   =           7

                                   Wald chi2(11)             =      277.16
                                   Prob > chi2                =      0.0000

Log likelihood = -3399.6342
```

	pov	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
1.mother		1.023185	.1183556	8.65	0.000	.7912122	1.255157
1.spouse		-1.172154	.1509384	-7.77	0.000	-1.467988	-.8763204
1.school		-.1123479	.0989736	-1.14	0.256	-.3063327	.0816368
hours		-.0170478	.004132	-4.13	0.000	-.0251464	-.0089492
year							
2		.2861683	.1000751	2.86	0.004	.0900246	.482312
3		.219169	.1040961	2.11	0.035	.0151444	.4231936
4		.2497039	.1090519	2.29	0.022	.0359661	.4634416
5		.1488229	.1161253	1.28	0.200	-.0787785	.3764243
1.black		.7280679	.1057163	6.89	0.000	.5208678	.935268
black#c.hours							
1		-.0155339	.00538	-2.89	0.004	-.0260785	-.0049892
age		-.0602152	.0470168	-1.28	0.200	-.1523664	.031936
_cons		-.1248085	.7601223	-0.16	0.870	-1.614621	1.365004
id							
var(_cons)		1.33912	.1358071			1.097728	1.633595

```
LR test vs. logistic model: chibar2(01) = 319.42      Prob >= chibar2 = 0.0000
```

It is obvious from the output, and not too surprising, that those who are mothers at the time of the survey, do not have a spouse, are Black, and work more hours, are more likely to be in poverty. But how much more likely? One percent? 50 percent? Or what? Further complicating matters is that the interaction between black and hours is significantly negative, suggesting that working more hours reduces poverty more for Black people than it does for White people. But how much? AAPs (Average Adjusted Predictions), AMEs (Average Marginal Effects), APRs (Adjusted Predictions at Representative values) and MERs (Marginal Effects at Representative values) can give us some guidance.

```
. margins mother spouse black, grand
```

```
Predictive margins                                Number of obs      =       5,755
Model VCE      : OIM

Expression     : Marginal predicted mean, predict()
```

		Delta-method		z	P> z	[95% Conf. Interval]	
		Margin	Std. Err.				
mother							
	0	.3420837	.0090595	37.76	0.000	.3243275	.3598399
	1	.5293023	.0198266	26.70	0.000	.490443	.5681617
spouse							
	0	.3975583	.0087569	45.40	0.000	.380395	.4147216
	1	.2132171	.0188862	11.29	0.000	.1762008	.2502333
black							
	0	.314291	.0124135	25.32	0.000	.2899609	.3386211
	1	.4223253	.0112836	37.43	0.000	.4002098	.4444407
_cons							
		.3778618	.0082933	45.56	0.000	.3616072	.3941164

These results are, I think, much easier to get a substantive feel for. The constant (which we got because we added the grand option) tells us that 37.8 percent of the subjects are in poverty at the time of the interview. But, for those who are mothers, the figure is almost 53 percent. Similarly, about 42 percent of Black subjects (compared to 31.4 percent of White subjects) are in poverty, as are about 40 percent of those without a spouse (compared with 21.3 percent of those who do). Keep in mind that these are the estimated differences AFTER all other variables in the model have been controlled for, e.g. even after controlling for hours worked and motherhood status, differences between White and Black people remain.)

You may also find it helpful to compute the AMEs, which, in the case of a dichotomous independent variable, are simply the differences between the adjusted predictions.

```
. margins, dydx(mother spouse black)
```

```
Average marginal effects      Number of obs      =      5,755
Model VCE      : OIM
```

```
Expression      : Marginal predicted mean, predict()
dy/dx w.r.t.    : 1.mother 1.spouse 1.black
```

		Delta-method				[95% Conf. Interval]	
		dy/dx	Std. Err.	z	P> z		
1.mother		.1872186	.0217485	8.61	0.000	.1445923	.2298448
1.spouse		-.1843413	.0203254	-9.07	0.000	-.2241783	-.1445042
1.black		.1080343	.0168314	6.42	0.000	.0750453	.1410233

Note: dy/dx for factor levels is the discrete change from the base level.

We again see that Black people are about 11 percentage points more likely on average to be in poverty than are White people, but we do not see what the predicted probabilities were for Black and White respondents separately.

What about hours worked, which is a continuous variable? We can estimate AMEs for it:

```
. margins, dydx(hours)
```

```
Average marginal effects      Number of obs      =      5,755
Model VCE      : OIM
```

```
Expression      : Marginal predicted mean, predict()
dy/dx w.r.t.    : hours
```

		Delta-method				[95% Conf. Interval]	
		dy/dx	Std. Err.	z	P> z		
hours		-.0046285	.0004939	-9.37	0.000	-.0055965	-.0036605

However, I personally do not find AMEs for continuous variables at all helpful. Instead, I prefer APRs.

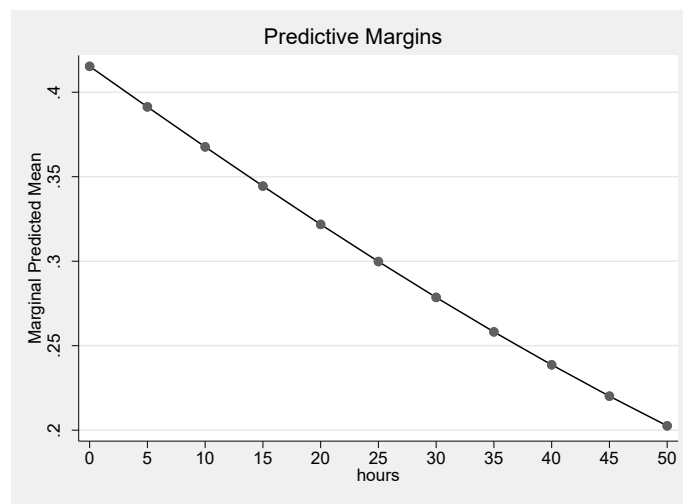
```
. margins, at(hours = (0(5)50)) vsquish
```

```
Predictive margins      Number of obs      =      5,755
Model VCE      : OIM
```

```
Expression      : Marginal predicted mean, predict()
1._at          : hours      =      0
2._at          : hours      =      5
3._at          : hours      =     10
4._at          : hours      =     15
5._at          : hours      =     20
6._at          : hours      =     25
7._at          : hours      =     30
8._at          : hours      =     35
9._at          : hours      =     40
10._at         : hours      =     45
11._at         : hours      =     50
```

		Delta-method				[95% Conf. Interval]	
		Margin	Std. Err.	z	P> z		
_at							
1		.4153367	.0095408	43.53	0.000	.396637	.4340364
2		.3913385	.008655	45.22	0.000	.374375	.408302
3		.3676703	.0085009	43.25	0.000	.3510089	.3843318
4		.3444526	.009041	38.10	0.000	.3267326	.3621727
5		.3217977	.0100689	31.96	0.000	.3020631	.3415324
6		.2998081	.01135	26.41	0.000	.2775625	.3220536
7		.2785748	.0127067	21.92	0.000	.25367	.3034795
8		.2581765	.0140241	18.41	0.000	.2306897	.2856633
9		.2386786	.0152318	15.67	0.000	.2088248	.2685324
10		.2201328	.0162884	13.51	0.000	.1882081	.2520575
11		.2025766	.0171718	11.80	0.000	.1689206	.2362326

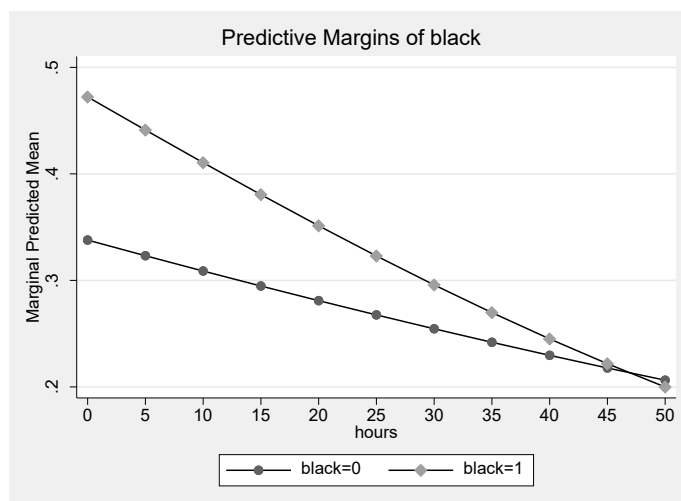
```
. marginsplot, noci scheme(sj) name(hours)
```



The output from margins and the graph produced by marginsplot provide a much clearer impact of the effect of hours worked. Those who do not work at all are predicted to have a 41.5% chance of being in poverty. Conversely, those who work 40 hours a week are predicted to have only a 23.8% chance.

It is also often helpful to get APRs for a combination of categorical and continuous variables:

```
. quietly margins black, at(hours = (0(5)50))
. marginsplot, noci scheme(sj) name(blackhours)
```



Remember that the validity of any results you get are contingent on the model being correct. But if this model is correct, it suggests that (at least in this sample) working provides a more powerful means for Black people to get out of poverty than it does for White people. When the average White or Black person does not work any hours, the predicted difference in poverty is about 13 percentage points. But, for those who work 40 or more hours a week, the predicted difference is almost zero.

Additional Material. Much more on margins can be found on my website at

<https://academicweb.nd.edu/~rwilliam/stats3/index.html>

As those notes show, I am a big fan of the `spost13` commands by Long and Freese. Many are basically shells for margins, and are easier to use and produce more aesthetically output. `mtable` seems to work with `melogit`, but other commands might not work with panel/multilevel models. To get a copy, from within Stata type `findit spost13_ado`. For more, see

<https://academicweb.nd.edu/~rwilliam/stats3/Margins04.pdf>

I am also a huge fan of Patrick Royston's `mcp` command, available from SSC. It is great for making the effects of continuous variables more interpretable. Unfortunately, it doesn't seem to work with `melogit`, but it does work after many other commands. See

<https://academicweb.nd.edu/~rwilliam/stats3/Margins03.pdf>

I'm primarily focusing on binary dependent variables in this course. To see how marginal effects can be used with ordinal models, check out

<https://academicweb.nd.edu/~rwilliam/stats3/Margins05.pdf>

What do marginal effects for continuous variables mean, and why am I not a fan of them? For a discussion, see

<https://academicweb.nd.edu/~rwilliam/stats3/Margins02.pdf>