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

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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 blacks benefit more (or less) than do whites 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
Log likelihood = -3399.6342                     Prob > chi2       =     0.0000
------------------------------------------------------------------------------
         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 blacks than it does whites. 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
             |     Margin   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      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 blacks (compared to 31.4 percent of whites) 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 whites and blacks 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
             |      dy/dx   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    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 those who are black are about 11 percentage points more likely on average to be in poverty than whites, but we do not see what the predicted probabilities were for blacks and whites 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
             |      dy/dx   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       hours |  -.0046285   .0004939    -9.37   0.000    -.0055965   -.0036605
------------------------------------------------------------------------------
```

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

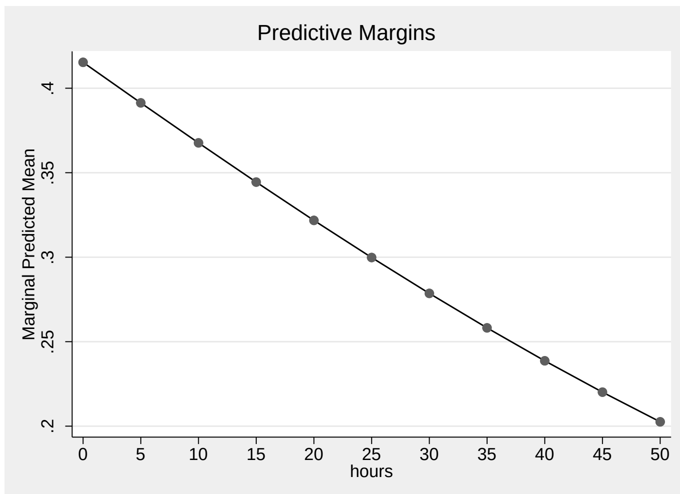
```
. margins, at(hours = (0(5)50)) vsquish

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
             |     Margin   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         _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
------------------------------------------------------------------------------
```

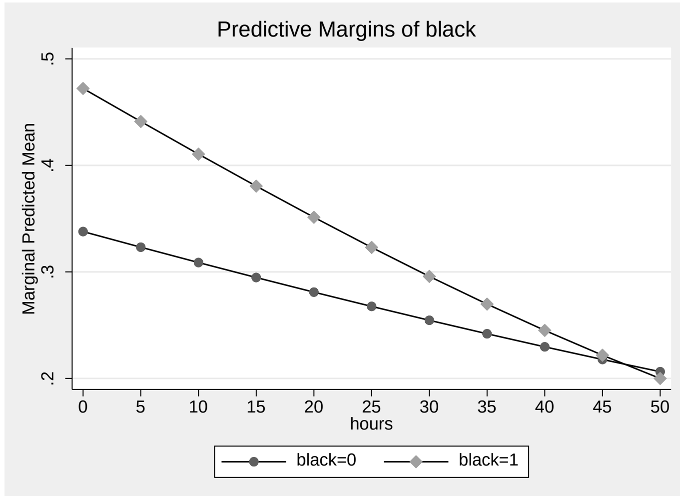
```
. marginsplot, noci scheme(sj) name(hours)
```



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 blacks to get out of poverty than it does for whites. When the average white or black do 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://www3.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://www3.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://www3.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://www3.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://www3.nd.edu/~rwilliam/stats3/Margins02.pdf