Multinomial logit models for longitudinal data

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Brazil Stata Conference

December 3, 2021

The multinomial logit model

- Primary use case: unordered categorical outcome variable.
- Panel data model in utility-maximization form: $U_{ijt} = x_{it}\beta_j + u_{ij} + \epsilon_{ijt}$
- u_{ij} is a panel-level error term, also referred to as panel-level unobservables, that captures (time-invariant) unobserved heterogeneity.
- Assuming a type-I extreme value distribution for ϵ_{ijt} and normalizing with respect to a base category gives rise to the logit model:

$$\Pr(y_{it} = m \,|\, x_{it}, \beta_j, u_{ij}) = F(y_{it} = m, x_{it}\beta_j + u_{ij}) =$$

$$\frac{1}{1 + \sum_{j=2}^{J} \exp(x_{it}\beta_j + u_{ij})} \text{ if } m = 1$$

$$\frac{\exp(x_{it}\beta_m + u_{im})}{1 + \sum_{j=2}^{J} \exp(x_{it}\beta_j + u_{ij})} \text{ if } m > 1$$

The random-effects estimator

- `xtmlogit` implements a random-effects and conditional fixed-effects estimator.
- The random-effects estimator assumes that the panel-level unobservables are uncorrelated with the covariates.
- The fixed-effects estimator relaxes this assumption and the unobservables can be arbitrarily correlated with the covariates.
- Random-effects estimator:

$$l_i = \int_{-\infty}^{\infty} \cdots \int_{-\infty}^{\infty} \left\{ \prod_{t=1}^{T_i} F(y_{it} = m, \mathbf{x}_{it}\beta_j + u_{ij}) \right\} \phi(u_i, \Sigma_u)\, du_i$$

- This integral has no closed form and we approximate it using quadrature.

The fixed-effects estimator

- Fixed-effects estimator:

$$\log\ l_i = \sum_{t=1}^{T_i}\sum_{j=2}^{J} Y_{ijt}\mathbf{x}_{it}\beta_j - \log \sum_{\tilde{Y}_{ijt}\in\Psi(c_i)} \exp\left(\sum_{t=1}^{T_i}\sum_{j=2}^{J}\tilde{Y}_{ijt}\mathbf{x}_{it}\beta_j\right)$$

- $\Psi(c_i)$ is a set of all permutations of individual i's observed sequence of outcomes that satisfies the condition $\sum_{t=1}^{T_i}\tilde{Y}_{it} = c_i$. That is,

$$\Psi(c_i) = \left\{ \tilde{Y}_i = (\tilde{Y}_{i1},\ldots,\tilde{Y}_{iT_i}) \,\middle|\, \sum_{t=1}^{T_i}\tilde{Y}_{it} = c_i \right\}$$

- where $\tilde{Y}_{it} = (\tilde{Y}_{i1t},\ldots,\tilde{Y}_{iJt})$ is a vector of indicators with respect to the permutations of the observed outcome sequence Y_i.
- For example, the sequence $Y_i = (3,2,3)$ has a total of three permutations (including the original sequence): $(2,3,3)$, $(3,2,3)$, and $(3,3,2)$

Curse of dimensionality: random-effects estimator

- For the random-effects estimator, the curse is rooted in J, the number of outcomes, because we have a $J - 1$ dimensional integral.
- Computation time can be high for more than just three or four outcomes.
- For example, with six outcomes, we have to approximate a five-dimensional integral.
- Using seven quadrature integration points, we would end up with $7^5 = 16,807$ integration points.
- If computation time becomes infeasible one might consider using a single, shared variance component, if appropriate (option `covariance(shared)`).

Curse of dimensionality: fixed-effects estimator

- The curse of dimensionality in case of the fixed-effects estimator is rooted mainly in T_i, the number of repeated observations, and potentially in J.
- The number of permutations in $\Psi(c_i)$ grows exponentially with T_i and can become infeasibly large.
- The number of permutations of panel i's observed vector of outcomes is:

$$K_i = \frac{T_i!}{c_{i1}! \cdots c_{ij}! \cdots c_{iJ}!}$$

- For example, for an individual with 15 repeated observations in a dataset with 6 outcomes, $j = 1, 2, \ldots, 6$, with the sequence of outcomes $Y_i = (3, 3, 3, 2, 4, 1, 1, 5, 4, 6, 6, 1, 1, 2, 4)$ the size of the set of permutations of this outcome vector is

$$K_i = \frac{15!}{4!\,2!\,3!\,3!\,1!\,2!} = 378{,}378{,}000$$

- Realistically, T_i should not be larger than around 9 or 10.

When to use which estimator

- If the assumptions of the random-effects estimator hold, both the random-effects and fixed-effects estimators are consistent, but the random-effects estimator is more efficient. If the assumptions do not hold, the random-effects estimator becomes inconsistent.
- If all we care about is estimating β_j, we should use the fixed-effects estimator because we have to make fewer assumptions.
- Practical consideration: beyond the gain in efficiency, if we want to perform marginal predictions or include time-constant covariates, the random-effects estimator is preferrable.
- With the fixed-effects estimator, we cannot make predictions that account for the panel-level unobservables because these are not parameterized.
- A potential way to decide between the two is to perform a Hausman test.

Some notable features

- In the context of the **random-effects** estimator, we can decide what restrictions to place on the variance-covariance matrix of the random effects:
  - `covariance(independent)`; distinct variances, the default
  - `covariance(unstructured)`; no restrictions
  - `covariance(exchangeable)`; equal variances and covariances
  - `covariance(identity)`; equal variances, covariance 0
  - `covariance(shared)`; one common random effect
- With the **fixed-effects** estimator, the curse of dimensionality can be alleviated to some degree by taking random samples from the permutation sets using option `rsample()`.
- `xtmlogit` can be used with `svy`
- `bayes: xtmlogit` (random-effects estimator)

Example data (1)

```
. webuse estatus
(Fictional employment status data)

. describe

Contains data from https://www.stata-press.com/data/r17/estatus.dta
 Observations:         4,761                  Fictional employment status data
    Variables:             8                  26 Feb 2021 15:17
--------------------------------------------------------------------------------
Variable      Storage   Display    Value
    name         type    format    label      Variable label
--------------------------------------------------------------------------------
id              int     %9.0g                 Respondent ID
year            int     %9.0g                 Year of survey
estatus         byte    %18.0g     alt        Employment status
hhchild         byte    %9.0g      noyes      Children <18 years old in
                                                household
hhincome        int     %10.0g                Annual household income (in
                                                $1,000s)
hhsigno         byte    %10.0g     noyes      Significant other living in
                                                household
bwinner         byte    %10.0g     noyes      Primary/sole breadwinner in
                                                household
age             byte    %10.0g                Age (in years)
--------------------------------------------------------------------------------
Sorted by: id  year

. tab estatus

 Employment status |      Freq.     Percent        Cum.
-------------------+-----------------------------------
Out of labor force |      1,682       35.33       35.33
        Unemployed |        703       14.77       50.09
          Employed |      2,376       49.91      100.00
-------------------+-----------------------------------
             Total |      4,761      100.00
```

Example data (2)

```
. list in 1/10, compress noobs

  id   year            estatus   hhc~d   hhi~e   hhs~o   bwi~r   age

   1   2002   Out of labor force     Yes      56     Yes     Yes    34
   1   2004   Out of labor force     Yes      62      No     Yes    36
   1   2006             Employed     Yes      68     Yes      No    38
   1   2008             Employed      No      73      No     Yes    40
   1   2010   Out of labor force      No      85     Yes      No    42

   2   2002             Employed      No      28     Yes      No    19
   2   2004   Out of labor force     Yes      26     Yes     Yes    21
   2   2006             Employed     Yes      31      No      No    23
   2   2008             Employed     Yes      36     Yes     Yes    25
   2   2010           Unemployed     Yes      42     Yes      No    27
```

Using mlogit

```
. mlogit  estatus i.hhchild age hhincome i.hhsigno i.bwinner

Iteration 0:   log likelihood = -4746.2288
Iteration 1:   log likelihood = -4586.1414
Iteration 2:   log likelihood = -4581.5114
Iteration 3:   log likelihood =  -4581.496
Iteration 4:   log likelihood =  -4581.496

Multinomial logistic regression                         Number of obs =  4,761
                                                        LR chi2(10)   = 329.47
                                                        Prob > chi2   = 0.0000
Log likelihood = -4581.496                              Pseudo R2     = 0.0347

------------------------------------------------------------------------------
     estatus | Coefficient  Std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
Out_of_lab~e |
     hhchild |
        Yes  |   .3603056   .0767921     4.69   0.000     .2097958    .5108155
         age |  -.0051251   .0050107    -1.02   0.306    -.0149459    .0046958
    hhincome |  -.0041118   .0012464    -3.30   0.001    -.0065546    -.001669
             |
     hhsigno |
        Yes  |   .4251824    .085001     5.00   0.000     .2585835    .5917814
             |
     bwinner |
        Yes  |  -.4341223   .0646731    -6.71   0.000    -.5608793   -.3073654
       _cons |  -.3054547   .2219434    -1.38   0.169    -.7404558    .1295464
-------------+----------------------------------------------------------------
Unemployed   |
     hhchild |
        Yes  |  -.0421006   .1026229    -0.41   0.682    -.2432378    .1590366
         age |   .0027158   .0066839     0.41   0.685    -.0103845     .015816
    hhincome |  -.0278535   .0020728   -13.44   0.000    -.0319161   -.0237909
             |
     hhsigno |
        Yes  |   .1070661   .1100785     0.97   0.331    -.1086839    .3228161
             |
     bwinner |
        Yes  |  -.2185759   .0879215    -2.49   0.013    -.3908989    -.046253
       _cons |   .0142404    .293933     0.05   0.961    -.5618577    .5903385
-------------+----------------------------------------------------------------
Employed     |  (base outcome)
------------------------------------------------------------------------------
```

Panel data model with random effects (1)

```
. xtset id
Panel variable: id (unbalanced)
. xtmlogit estatus i.hhchild age hhincome i.hhsigno i.bwinner
Fitting comparison model ...
Refining starting values:
Grid node 0:   log likelihood = -4483.1721
Grid node 1:   log likelihood = -4516.6753
Fitting full model:
Iteration 0:   log likelihood = -4483.1721
Iteration 1:   log likelihood = -4474.3849
Iteration 2:   log likelihood = -4468.9353
Iteration 3:   log likelihood = -4468.8415
Iteration 4:   log likelihood = -4468.8413
Random-effects multinomial logistic regression       Number of obs     =  4,761
Group variable: id                                   Number of groups =    800
Random effects u_i ~ Gaussian                        Obs per group:
                                                                  min =      5
                                                                  avg =    6.0
                                                                  max =      7
Integration method: mvaghermite                      Integration pts. =      7
                                                     Wald chi2(10)    = 239.26
Log likelihood = -4468.8413                          Prob > chi2      = 0.0000

------------------------------------------------------------------------------
     estatus | Coefficient  Std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
             |
```

Panel data model with random effects (2)

estatus	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
Out_of_lab~e						
hhchild						
Yes	.4628125	.0962758	4.81	0.000	.2741154	.6515096
age	-.004825	.0066428	-0.73	0.468	-.0178446	.0081946
hhincome	-.0046922	.001839	-2.55	0.011	-.0082965	-.0010879
hhsigno						
Yes	.4967056	.0946442	5.25	0.000	.3112063	.6822049
bwinner						
Yes	-.4740919	.0727992	-6.51	0.000	-.6167756	-.3314082
_cons	-.4787579	.2845139	-1.68	0.092	-1.036395	.0788792
Unemployed						
hhchild						
Yes	-.0401989	.119596	-0.34	0.737	-.2746027	.1942049
age	.0042644	.0081818	0.52	0.602	-.0117716	.0203004
hhincome	-.0308468	.0026529	-11.63	0.000	-.0360463	-.0256473
hhsigno						
Yes	.0968	.1192659	0.81	0.417	-.1369568	.3305568
bwinner						
Yes	-.2252587	.0951984	-2.37	0.018	-.4118441	-.0386733
_cons	-.0953821	.3508736	-0.27	0.786	-.7830817	.5923175
Employed	(base outcome)					
var(u1)	.8587807	.1090216			.6696113	1.101392
var(u2)	.7370366	.1388917			.5094287	1.066338

LR test vs. multinomial logit: chi2(2) = 225.31 Prob > chi2 = 0.0000

Note: LR test is conservative and provided only for reference.

Displaying relative-risk ratios

```
. xtmlogit, rrr

Random-effects multinomial logistic regression       Number of obs     =  4,761
Group variable: id                                   Number of groups =    800

Random effects u_i ~ Gaussian                        Obs per group:
                                                                  min =      5
                                                                  avg =    6.0
                                                                  max =      7

Integration method: mvaghermite                      Integration pts. =      7

                                                     Wald chi2(10)     = 239.26
Log likelihood = -4468.8413                          Prob > chi2       = 0.0000

-----------------------------------------------------------------------------
     estatus |       RRR   Std. err.      z    P>|z|     [95% conf. interval]
-------------+---------------------------------------------------------------
Out_of_lab~e |
     hhchild |
        Yes  |   1.588535   .1529375     4.81   0.000     1.315367    1.918435
         age |   .9951866   .0066108    -0.73   0.468     .9823137    1.008228
    hhincome |   .9953188   .0018303    -2.55   0.011     .9917379    .9989127
             |
     hhsigno |
        Yes  |   1.643299   .1555288     5.25   0.000     1.365071    1.978235
             |
     bwinner |
        Yes  |   .6224501   .0453138    -6.51   0.000     .5396818    .7179121
       _cons |   .6195525   .1762713    -1.68   0.092     .3547312    1.082074
-------------+---------------------------------------------------------------
Unemployed   |
     hhchild |
        Yes  |   .9605983   .1148837    -0.34   0.737     .7598739    1.214345
         age |   1.004274   .0082168     0.52   0.602     .9882974    1.020508
    hhincome |   .9696241   .0025723   -11.63   0.000     .9645956    .9746788
             |
     hhsigno |
        Yes  |    1.10164   .1313881     0.81   0.417     .8720079    1.391743
             |
     bwinner |
        Yes  |   .7983097   .0759978    -2.37   0.018     .6624275    .9620649
       _cons |   .9090255   .3189531    -0.27   0.786     .4569955    1.808174
-------------+---------------------------------------------------------------
Employed     |  (base outcome)
-------------+---------------------------------------------------------------
     var(u1) |   .8587807   .1090216                       .6696113    1.101392
     var(u2) |   .7370366   .1388917                       .5094287    1.066338
-----------------------------------------------------------------------------
Note: Estimates are transformed only in the first 3 equations to
      relative-risk ratios.
Note: _cons estimates baseline relative risk (conditional on zero random
      effects).
LR test vs. multinomial logit: chi2(2) = 225.31          Prob > chi2 = 0.0000
Note: LR test is conservative and provided only for reference.
```

Unstructured covariance estimation (1)

```
. xtmlogit estatus i.hhchild age hhincome i.hhsigno i.bwinner, covariance(unstr
> uctured)
Fitting comparison model ...
Refining starting values:
Grid node 0:   log likelihood = -4483.1721
Grid node 1:   log likelihood = -4516.6753
Fitting full model:
Iteration 0:   log likelihood = -4483.1721
Iteration 1:   log likelihood = -4454.5313
Iteration 2:   log likelihood = -4438.9076
Iteration 3:   log likelihood = -4438.2905
Iteration 4:   log likelihood = -4438.2887
Iteration 5:   log likelihood = -4438.2887
Random-effects multinomial logistic regression       Number of obs     =  4,761
Group variable: id                                   Number of groups =    800
Random effects u_i ~ Gaussian                        Obs per group:
                                                                  min =      5
                                                                  avg =    6.0
                                                                  max =      7
Integration method: mvaghermite                      Integration pts. =      7
                                                     Wald chi2(10)     = 242.93
Log likelihood = -4438.2887                          Prob > chi2       = 0.0000
------------------------------------------------------------------------------
     estatus | Coefficient  Std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
```

Unstructured covariance estimation (2)

estatus	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
Out_of_lab~e						
hhchild						
Yes	.4924799	.1002988	4.91	0.000	.295898	.6890619
age	-.004219	.0070064	-0.60	0.547	-.0179513	.0095133
hhincome	-.006046	.001992	-3.04	0.002	-.0099503	-.0021417
hhsigno						
Yes	.5036976	.0966982	5.21	0.000	.3141726	.6932225
bwinner						
Yes	-.489057	.0745454	-6.56	0.000	-.6351632	-.3429507
_cons	-.3930378	.298386	-1.32	0.188	-.9778636	.191788
Unemployed						
hhchild						
Yes	.0399687	.1238417	0.32	0.747	-.2027565	.2826939
age	.0045538	.0085081	0.54	0.592	-.0121219	.0212294
hhincome	-.0315377	.0027426	-11.50	0.000	-.0369131	-.0261624
hhsigno						
Yes	.1495817	.1214242	1.23	0.218	-.0884053	.3875687
bwinner						
Yes	-.2552257	.0968165	-2.64	0.008	-.4449826	-.0654689
_cons	-.0417024	.3633406	-0.11	0.909	-.7538368	.670432
Employed	(base outcome)					
var(u1)	1.132081	.1331468			.899012	1.425572
var(u2)	1.102612	.1698422			.8152803	1.49121
cov(u1,u2)	.7871916	.1222148	6.44	0.000	.547655	1.026728

LR test vs. multinomial logit: chi2(3) = 286.41 Prob > chi2 = 0.0000

Note: LR test is conservative and provided only for reference.

Standard deviation and correlation

```
. estat sd
```

estatus	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
sd(u1)	1.063993	.0625694			.9481624	1.193973
sd(u2)	1.050053	.0808731			.9029287	1.221151
corr(u1,u2)	.7045801	.0632646	11.14	0.000	.5581225	.8084624

Panel data model with conditional fixed effects (1)

```
. xtmlogit estatus i.hhchild age hhincome i.hhsigno i.bwinner, fe
note: 80 groups (451 obs) omitted because of no variation in the outcome
      variable over time.

Computing initial values ...

Setting up 26,168 permutations:
....10%....20%....30%....40%....50%....60%....70%....80%....90%....100%

Fitting full model:

Iteration 0:   log likelihood = -2136.5919
Iteration 1:   log likelihood = -2136.2728
Iteration 2:   log likelihood = -2136.2728

Fixed-effects multinomial logistic regression        Number of obs     =  4,310
Group variable: id                                    Number of groups =    720

                                                      Obs per group:
                                                                   min =      5
                                                                   avg =    6.0
                                                                   max =      7

                                                      LR chi2(10)      = 103.29
Log likelihood = -2136.2728                           Prob > chi2      = 0.0000

------------------------------------------------------------------------------
     estatus | Coefficient  Std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
```

Panel data model with conditional fixed effects (2)

estatus	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
Out_of_lab~e						
hhchild						
Yes	.5881852	.1258696	4.67	0.000	.3414854	.834885
age	-.0003842	.0147741	-0.03	0.979	-.0293409	.0285725
hhincome	-.0122043	.0088464	-1.38	0.168	-.029543	.0051344
hhsigno						
Yes	.5090034	.100111	5.08	0.000	.3127893	.7052174
bwinner						
Yes	-.4655745	.0782841	-5.95	0.000	-.6190085	-.3121406
Unemployed						
hhchild						
Yes	.163612	.1638934	1.00	0.318	-.1576132	.4848372
age	.0063355	.019404	0.33	0.744	-.0316957	.0443667
hhincome	-.029742	.0120031	-2.48	0.013	-.0532676	-.0062164
hhsigno						
Yes	.1173192	.1301364	0.90	0.367	-.1377435	.3723819
bwinner						
Yes	-.2489958	.1030027	-2.42	0.016	-.4508773	-.0471142
Employed	(base outcome)					

Fixed-effects model with permutation sampling (1)

```
. xtset id year

Panel variable: id (unbalanced)
 Time variable: year, 2002 to 2014, but with gaps
         Delta: 1 unit

. xtmlogit estatus i.hhchild age hhincome i.hhsigno i.bwinner, fe rsample(10, r
> seed(123))
note: option vce() set to vce(robust) because of permutation sampling.
note: 80 groups (451 obs) omitted because of no variation in the outcome
      variable over time.

Computing initial values ...

Setting up 3,495 permutations:
....10%....20%....30%....40%....50%....60%....70%....80%....90%....100%

Fitting full model:

Iteration 0:   log pseudolikelihood = -908.26163
Iteration 1:   log pseudolikelihood =  -906.4585
Iteration 2:   log pseudolikelihood = -906.45801
Iteration 3:   log pseudolikelihood = -906.45801

Fixed-effects multinomial logistic regression        Number of obs     =  4,310
Group variable: id                                   Number of groups =    720

                                                     Obs per group:
                                                                  min =      5
                                                                  avg =    6.0
                                                                  max =      7

                                                     Wald chi2(10)     =  72.91
Log pseudolikelihood = -906.45801                    Prob > chi2       = 0.0000

                                    (Std. err. adjusted for 720 clusters in id)
-------------------------------------------------------------------------------
             |               Robust
     estatus | Coefficient  std. err.      z    P>|z|     [95% conf. interval]
-------------+-----------------------------------------------------------------
             |
```

Fixed-effects model with permutation sampling (2)

estatus	Coefficient	Robust std. err.	z	P>|z|	[95% conf.	interval]
Out_of_lab~e						
hhchild						
Yes	.5827048	.1487376	3.92	0.000	.2911845	.8742251
age	-.0055092	.0168589	-0.33	0.744	-.0385521	.0275337
hhincome	-.0142493	.0100457	-1.42	0.156	-.0339386	.0054399
hhsigno						
Yes	.4441511	.1213382	3.66	0.000	.2063325	.6819696
bwinner						
Yes	-.4613157	.0978061	-4.72	0.000	-.6530122	-.2696193
Unemployed						
hhchild						
Yes	.1714144	.1831194	0.94	0.349	-.187493	.5303217
age	-.0046656	.0217006	-0.21	0.830	-.0471979	.0378668
hhincome	-.0344681	.0131707	-2.62	0.009	-.0602821	-.0086541
hhsigno						
Yes	-.0760533	.1396542	-0.54	0.586	-.3497705	.197664
bwinner						
Yes	-.2889772	.1178606	-2.45	0.014	-.5199797	-.0579747
Employed	(base outcome)					

Performing a Hausman test

```
. qui xtmlogit estatus i.hhchild age hhincome i.hhsigno i.bwinner, fe

. estimates store FE

. qui xtmlogit estatus i.hhchild age hhincome i.hhsigno i.bwinner

. estimates store RE

. hausman FE RE, alleqs

                 ---- Coefficients ----
             |      (b)          (B)            (b-B)     sqrt(diag(V_b-V_B))
             |      FE           RE          Difference       Std. err.
-------------+----------------------------------------------------------------
Out_of_lab~e |
   1.hhchild |   .5881852     .4628125        .1253727        .0810809
         age |  -.0003842    -.004825         .0044408        .0131965
    hhincome |  -.0122043    -.0046922       -.0075122        .0086532
   1.hhsigno |   .5090034     .4967056        .0122977        .0326296
   1.bwinner |  -.4655745    -.4740919        .0085173        .0287868
-------------+----------------------------------------------------------------
Unemployed   |
   1.hhchild |    .163612    -.0401989         .203811        .1120618
         age |   .0063355     .0042644        .0020711        .0175947
    hhincome |   -.029742    -.0308468        .0011048        .0117062
   1.hhsigno |   .1173192        .0968        .0205192        .0520686
   1.bwinner |  -.2489958    -.2252587       -.0237371        .0393297
------------------------------------------------------------------------------
                          b = Consistent under H0 and Ha; obtained from xtmlogit.
           B = Inconsistent under Ha, efficient under H0; obtained from xtmlogit.

Test of H0: Difference in coefficients not systematic

   chi2(10) = (b-B)'[(V_b-V_B)^(-1)](b-B)
            =   8.05
Prob > chi2 = 0.6238
```

Using `margins` after `xtmlogit, re`

```
. qui xtmlogit estatus i.hhchild age hhincome i.hhsigno i.bwinner

. margins i.hhchild

Predictive margins                                      Number of obs = 4,761
Model VCE: OIM

1._predict: Pr(estatus==Out_of_labor_force), predict(pr outcome(1))
2._predict: Pr(estatus==Unemployed), predict(pr outcome(2))
3._predict: Pr(estatus==Employed), predict(pr outcome(3))

------------------------------------------------------------------------------
             |            Delta-method
             |     Margin   std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
   _predict#|
     hhchild |
       1#No  |   .3021986   .0131047    23.06   0.000     .2765138    .3278834
      1#Yes  |   .3912783   .0119865    32.64   0.000     .3677852    .4147714
       2#No  |   .1630791   .0101239    16.11   0.000     .1432367    .1829216
      2#Yes  |    .139782   .0079417    17.60   0.000     .1242167    .1553474
       3#No  |   .5347223   .0136504    39.17   0.000      .507968    .5614766
      3#Yes  |   .4689397   .0116018    40.42   0.000     .4462006    .4916787
------------------------------------------------------------------------------
```

- Note: using `margins` after `xtmlogit, fe` is not advisable.

predict

- `xtmlogit, re`
  - `pr` marginal probability of the specified outcome; the default
  - `pcr` conditional probability of the specified outcome
  - `pu0` probability of the specified outcome, assuming zero random effects
  - `xb` linear prediction for the specified outcome, including random effects
  - `xb0` linear prediction for the specified outcome, assuming zero random effects
- `xtmlogit, fe`
  - `pu0` probability of the specified outcome, assuming zero fixed effects; the default
  - `xb` linear prediction for the specified outcome, assuming zero random effects
- Option `outcome()` to specify a particular outcome.
- Or use `stub*` to get predictions for all outcomes.

Thank You!