```
      name:  <unnamed>
       log:  /Users/elisabethgidengil/Documents/Blais MCRI/Region/Ontario MNL.smcl
  log type:  smcl
 opened on:   1 Sep 2016, 17:28:03

  1 . do "/var/folders/16/42410mvx0xn3d_mb9nryycwr0000gn/T//SD03576.000000"

  2 . ***ONTARIO
  3 .
  4 . gen ONTvote=1 if PQ6==3
    (4,301 missing values generated)

  5 . replace ONTvote=2 if PQ6==1
    (905 real changes made)

  6 . replace ONTvote=3 if PQ6==2
    (891 real changes made)

  7 . lab def ONTvote 1 "Liberal" 2 "Conservative" 3 "NDP"

  8 .
  9 . ***Social background
 10 .
 11 . mlogit ONTvote i.female i.older i.lowinc i.missingincome i.HSorless i.university
    >  i.French i.visible i.catholic i.noreligion i.working i.union i.bigcity if Provi
    > nce==35  [iweight=regionWT], robust

    Iteration 0:   log pseudolikelihood =  -1145.875
    Iteration 1:   log pseudolikelihood =  -1062.841
    Iteration 2:   log pseudolikelihood = -1060.8136
    Iteration 3:   log pseudolikelihood = -1060.8077
    Iteration 4:   log pseudolikelihood = -1060.8077

    Multinomial logistic regression                 Number of obs     =      1,144
                                                    Wald chi2(26)     =     116.76
                                                    Prob > chi2       =     0.0000
    Log pseudolikelihood = -1060.8077               Pseudo R2         =     0.0742
```

ONTvote	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
1	(base outcome)					
2						
1.female	-.4907329	.1650925	-2.97	0.003	-.8143084	-.1671575
1.older	.1234334	.1953302	0.63	0.527	-.2594068	.5062736
1.lowinc	-.1563893	.1808591	-0.86	0.387	-.5108665	.198088

1.missingincome	.1619339	.2912861	0.56	0.578	-.4089763	.7328441
1.HSorless	.3877064	.2263527	1.71	0.087	-.0559368	.8313496
1.university	-.3845468	.1670198	-2.30	0.021	-.7118997	-.057194
1.French	-1.163316	.5708057	-2.04	0.042	-2.282075	-.0445576
1.visible	-.3590895	.2473988	-1.45	0.147	-.8439823	.1258033
1.catholic	-.3886657	.209498	-1.86	0.064	-.7992742	.0219427
1.noreligion	-.8651527	.2039387	-4.24	0.000	-1.264865	-.4654402
1.working	.2573204	.1973012	1.30	0.192	-.1293829	.6440237
1.union	-.3155659	.207345	-1.52	0.128	-.7219546	.0908228
1.bigcity	-.5883791	.1749853	-3.36	0.001	-.931344	-.2454143
_cons	.5329772	.2838838	1.88	0.060	-.0234249	1.089379
3						
1.female	.1586273	.1982351	0.80	0.424	-.2299063	.547161
1.older	-.7491661	.2429752	-3.08	0.002	-1.225389	-.2729436
1.lowinc	.4659285	.2248509	2.07	0.038	.0252287	.9066282
1.missingincome	.1721626	.3647823	0.47	0.637	-.5427975	.8871228
1.HSorless	.8175214	.2461707	3.32	0.001	.3350356	1.300007
1.university	.0723744	.1968599	0.37	0.713	-.3134638	.4582127
1.French	.3089149	.4715213	0.66	0.512	-.6152499	1.23308
1.visible	-.6100889	.2946202	-2.07	0.038	-1.187534	-.032644
1.catholic	-.0350755	.2604633	-0.13	0.893	-.5455741	.4754231
1.noreligion	.1462107	.2218478	0.66	0.510	-.2886031	.5810244
1.working	-.6226406	.2358086	-2.64	0.008	-1.084817	-.1604643
1.union	.6321511	.2330499	2.71	0.007	.1753816	1.088921
1.bigcity	.2037119	.2004043	1.02	0.309	-.1890733	.596497
_cons	-1.330287	.3433566	-3.87	0.000	-2.003254	-.6573204

```
12 . mlogit ONTvote i.female i.older i.lowinc i.missingincome i.HSorless i.university
   >  i.French i.visible i.catholic i.noreligion i.working i.union i.bigcity if Provi
   > nce==35  [iweight=regionWT], baseoutcome(2) robust

Iteration 0:   log pseudolikelihood =  -1145.875
Iteration 1:   log pseudolikelihood =  -1062.841
Iteration 2:   log pseudolikelihood = -1060.8136
Iteration 3:   log pseudolikelihood = -1060.8077
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Multinomial logistic regression                 Number of obs     =      1,144
                                                Wald chi2(26)     =     116.76
                                                Prob > chi2       =     0.0000
Log pseudolikelihood = -1060.8077               Pseudo R2         =     0.0742
```

ONTvote	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
1						

```
            1.female |   .4907329   .1650925     2.97   0.003     .1671575    .8143084
             1.older |  -.1234334   .1953302    -0.63   0.527    -.5062736    .2594068
            1.lowinc |   .1563893   .1808591     0.86   0.387     -.198088    .5108665
     1.missingincome |  -.1619339   .2912861    -0.56   0.578    -.7328441    .4089763
          1.HSorless |  -.3877064   .2263527    -1.71   0.087    -.8313496    .0559368
        1.university |   .3845468   .1670198     2.30   0.021      .057194    .7118997
            1.French |   1.163316   .5708057     2.04   0.042     .0445576    2.282075
           1.visible |   .3590895   .2473988     1.45   0.147    -.1258033    .8439823
          1.catholic |   .3886657    .209498     1.86   0.064    -.0219427    .7992742
        1.noreligion |   .8651527   .2039387     4.24   0.000     .4654402    1.264865
           1.working |  -.2573204   .1973012    -1.30   0.192    -.6440237    .1293829
             1.union |   .3155659    .207345     1.52   0.128    -.0908228    .7219546
           1.bigcity |   .5883791   .1749853     3.36   0.001     .2454143     .931344
               _cons |  -.5329772   .2838838    -1.88   0.060    -1.089379    .0234249
---------------------+----------------------------------------------------------------
2                    |  (base outcome)
---------------------+----------------------------------------------------------------
3                    |
            1.female |   .6493603   .2141199     3.03   0.002      .229693    1.069028
             1.older |  -.8725995   .2601573    -3.35   0.001    -1.382498   -.3627006
            1.lowinc |   .6223177   .2344535     2.65   0.008     .1627973    1.081838
     1.missingincome |   .0102287    .407657     0.03   0.980    -.7887643    .8092218
          1.HSorless |    .429815   .2511277     1.71   0.087    -.0623863    .9220164
        1.university |   .4569213    .211916     2.16   0.031     .0415735    .8722691
            1.French |   1.472231   .6386799     2.31   0.021     .2204415    2.724021
           1.visible |  -.2509994   .3106386    -0.81   0.419    -.8598399    .3578411
          1.catholic |   .3535903   .2741982     1.29   0.197    -.1838283    .8910088
        1.noreligion |   1.011363   .2545735     3.97   0.000     .5124085    1.510318
           1.working |   -.879961   .2518344    -3.49   0.000    -1.373547   -.3863748
             1.union |    .947717   .2482082     3.82   0.000     .4612378    1.434196
           1.bigcity |    .792091   .2159607     3.67   0.000     .3688157    1.215366
               _cons |  -1.863264   .3655981    -5.10   0.000    -2.579823   -1.146705
--------------------------------------------------------------------------------------

13 .
14 . margins, dydx(female)

Average marginal effects                        Number of obs     =      1,144
Model VCE    : Robust

dy/dx w.r.t. : 1.female
1._predict   : Pr(ONTvote==1), predict(pr outcome(1))
2._predict   : Pr(ONTvote==2), predict(pr outcome(2))
3._predict   : Pr(ONTvote==3), predict(pr outcome(3))

------------------------------------------------------------------------------
             |            Delta-method
             |      dy/dx   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
```

```
    1.female   |
      _predict |
            1  |   .0642815   .0335801     1.91   0.056    -.0015344    .1300973
            2  |  -.1116807   .0322974    -3.46   0.001    -.1749824    -.048379
            3  |   .0473992   .0244325     1.94   0.052    -.0004876    .0952861
------------------------------------------------------------------------------
Note: dy/dx for factor levels is the discrete change from the base level.

15 . margins, dydx(older)

Average marginal effects                        Number of obs     =      1,144
Model VCE    : Robust

dy/dx w.r.t. : 1.older
1._predict   : Pr(ONTvote==1), predict(pr outcome(1))
2._predict   : Pr(ONTvote==2), predict(pr outcome(2))
3._predict   : Pr(ONTvote==3), predict(pr outcome(3))

------------------------------------------------------------------------------
               |            Delta-method
               |      dy/dx   Std. Err.      z    P>|z|     [95% Conf. Interval]
---------------+--------------------------------------------------------------
    1.older    |
      _predict |
            1  |   .0365243   .0401564     0.91   0.363    -.0421809    .1152295
            2  |   .0651249   .0391284     1.66   0.096    -.0115653    .1418151
            3  |  -.1016491   .0280844    -3.62   0.000    -.1566935   -.0466047
------------------------------------------------------------------------------
Note: dy/dx for factor levels is the discrete change from the base level.

16 . margins, dydx(lowinc)

Average marginal effects                        Number of obs     =      1,144
Model VCE    : Robust

dy/dx w.r.t. : 1.lowinc
1._predict   : Pr(ONTvote==1), predict(pr outcome(1))
2._predict   : Pr(ONTvote==2), predict(pr outcome(2))
3._predict   : Pr(ONTvote==3), predict(pr outcome(3))

------------------------------------------------------------------------------
               |            Delta-method
               |      dy/dx   Std. Err.      z    P>|z|     [95% Conf. Interval]
---------------+--------------------------------------------------------------
    1.lowinc   |
      _predict |
            1  |  -.0117621   .0381253    -0.31   0.758    -.0864862    .0629621
            2  |  -.0570831   .0353756    -1.61   0.107    -.1264179    .0122518
            3  |   .0688451   .0268888     2.56   0.010      .016144    .1215462
```

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

17 . margins, dydx(HSorless)

```
Average marginal effects                        Number of obs     =      1,144
Model VCE    : Robust

dy/dx w.r.t. : 1.HSorless
1._predict   : Pr(ONTvote==1), predict(pr outcome(1))
2._predict   : Pr(ONTvote==2), predict(pr outcome(2))
3._predict   : Pr(ONTvote==3), predict(pr outcome(3))
```

	dy/dx	Delta-method Std. Err.	z	P>|z|	[95% Conf.	Interval]
1.HSorless						
_predict						
1	**-.1276428**	**.0463455**	**-2.75**	**0.006**	**-.2184784**	**-.0368073**
2	**.0350136**	**.0432091**	**0.81**	**0.418**	**-.0496748**	**.1197019**
3	**.0926292**	**.0338642**	**2.74**	**0.006**	**.0262566**	**.1590019**

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

18 . margins, dydx(university)

```
Average marginal effects                        Number of obs     =      1,144
Model VCE    : Robust

dy/dx w.r.t. : 1.university
1._predict   : Pr(ONTvote==1), predict(pr outcome(1))
2._predict   : Pr(ONTvote==2), predict(pr outcome(2))
3._predict   : Pr(ONTvote==3), predict(pr outcome(3))
```

	dy/dx	Delta-method Std. Err.	z	P>|z|	[95% Conf.	Interval]
1.university						
_predict						
1	**.0528**	**.0349957**	**1.51**	**0.131**	**-.0157904**	**.1213903**
2	**-.0829489**	**.0318803**	**-2.60**	**0.009**	**-.1454331**	**-.0204647**
3	**.030149**	**.0259592**	**1.16**	**0.245**	**-.0207301**	**.081028**

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

19 . margins, dydx(French)

```
Average marginal effects                        Number of obs     =      1,144
Model VCE    : Robust

dy/dx w.r.t. : 1.French
1._predict   : Pr(ONTvote==1), predict(pr outcome(1))
2._predict   : Pr(ONTvote==2), predict(pr outcome(2))
3._predict   : Pr(ONTvote==3), predict(pr outcome(3))
```

	dy/dx	Delta-method Std. Err.	z	P>|z|	[95% Conf.	Interval]
1.French						
_predict						
1	.1097041	.0935647	1.17	0.241	-.0736792	.2930875
2	-.2134151	.069675	-3.06	0.002	-.3499755	-.0768548
3	.103711	.0817162	1.27	0.204	-.0564497	.2638717

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

20 . margins, dydx(catholic)

Average marginal effects                        Number of obs     =      1,144
Model VCE    : Robust

dy/dx w.r.t. : 1.catholic
1._predict   : Pr(ONTvote==1), predict(pr outcome(1))
2._predict   : Pr(ONTvote==2), predict(pr outcome(2))
3._predict   : Pr(ONTvote==3), predict(pr outcome(3))
```

	dy/dx	Delta-method Std. Err.	z	P>|z|	[95% Conf.	Interval]
1.catholic						
_predict						
1	.0619421	.0439153	1.41	0.158	-.0241304	.1480145
2	-.0773337	.0387253	-2.00	0.046	-.153234	-.0014334
3	.0153916	.0336114	0.46	0.647	-.0504855	.0812688

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

21 . margins, dydx(noreligion)

Average marginal effects                        Number of obs     =      1,144
Model VCE    : Robust

dy/dx w.r.t. : 1.noreligion
1._predict   : Pr(ONTvote==1), predict(pr outcome(1))
```

```
2._predict   : Pr(ONTvote==2), predict(pr outcome(2))
3._predict   : Pr(ONTvote==3), predict(pr outcome(3))
```

	dy/dx	Delta-method Std. Err.	z	P>|z|	[95% Conf.	Interval]
1.noreligion						
_predict						
1	.1162767	.0393023	2.96	0.003	.0392456	.1933078
2	-.1820263	.0357052	-5.10	0.000	-.2520073	-.1120453
3	.0657496	.0303552	2.17	0.030	.0062545	.1252447

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

```
22 . margins, dydx(visible)

Average marginal effects                      Number of obs     =      1,144
Model VCE    : Robust

dy/dx w.r.t. : 1.visible
1._predict   : Pr(ONTvote==1), predict(pr outcome(1))
2._predict   : Pr(ONTvote==2), predict(pr outcome(2))
3._predict   : Pr(ONTvote==3), predict(pr outcome(3))
```

	dy/dx	Delta-method Std. Err.	z	P>|z|	[95% Conf.	Interval]
1.visible						
_predict						
1	.1036737	.0516995	2.01	0.045	.0023445	.2050028
2	-.0463531	.0471246	-0.98	0.325	-.1387156	.0460094
3	-.0573206	.029958	-1.91	0.056	-.1160372	.0013961

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

```
23 . margins, dydx(working)

Average marginal effects                      Number of obs     =      1,144
Model VCE    : Robust

dy/dx w.r.t. : 1.working
1._predict   : Pr(ONTvote==1), predict(pr outcome(1))
2._predict   : Pr(ONTvote==2), predict(pr outcome(2))
3._predict   : Pr(ONTvote==3), predict(pr outcome(3))
```

	Delta-method

	dy/dx	Std. Err.	z	P>|z|	[95% Conf.	Interval]
1.working						
_predict						
1	**.0102974**	**.0405772**	**0.25**	**0.800**	**-.0692324**	**.0898271**
2	**.0868698**	**.0379438**	**2.29**	**0.022**	**.0125013**	**.1612384**
3	**-.0971672**	**.0297122**	**-3.27**	**0.001**	**-.1554019**	**-.0389324**

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

```
24 . margins, dydx(union)

Average marginal effects                      Number of obs     =      1,144
Model VCE    : Robust

dy/dx w.r.t. : 1.union
1._predict   : Pr(ONTvote==1), predict(pr outcome(1))
2._predict   : Pr(ONTvote==2), predict(pr outcome(2))
3._predict   : Pr(ONTvote==3), predict(pr outcome(3))
```

	Delta-method dy/dx	Std. Err.	z	P>|z|	[95% Conf.	Interval]
1.union						
_predict						
1	**-.0126709**	**.0421779**	**-0.30**	**0.764**	**-.0953381**	**.0699963**
2	**-.0998109**	**.0367948**	**-2.71**	**0.007**	**-.1719275**	**-.0276944**
3	**.1124818**	**.0355918**	**3.16**	**0.002**	**.0427233**	**.1822404**

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

```
25 . margins, dydx(bigcity)

Average marginal effects                      Number of obs     =      1,144
Model VCE    : Robust

dy/dx w.r.t. : 1.bigcity
1._predict   : Pr(ONTvote==1), predict(pr outcome(1))
2._predict   : Pr(ONTvote==2), predict(pr outcome(2))
3._predict   : Pr(ONTvote==3), predict(pr outcome(3))
```

	Delta-method dy/dx	Std. Err.	z	P>|z|	[95% Conf.	Interval]
1.bigcity						
_predict						
1	**.072221**	**.0359329**	**2.01**	**0.044**	**.0017938**	**.1426482**

```
           2 |   -.131917   .0323283    -4.08   0.000    -.1952793   -.0685548
           3 |    .059696   .0269555     2.21   0.027     .0068643    .1125277
------------------------------------------------------------------------------
Note: dy/dx for factor levels is the discrete change from the base level.

26 .
27 . *** Values
28 .
29 . mlogit ONTvote i.female i.older i.lowinc i.missingincome i.HSorless i.university
>  i.French i.visible i.catholic i.noreligion i.working i.union i.bigcity antiredi
> stribute if Province==35  [iweight=regionWT], robust

Iteration 0:   log pseudolikelihood =  -1145.875
Iteration 1:   log pseudolikelihood = -1012.6823
Iteration 2:   log pseudolikelihood = -1010.1127
Iteration 3:   log pseudolikelihood = -1010.1095
Iteration 4:   log pseudolikelihood = -1010.1095

Multinomial logistic regression                 Number of obs     =      1,144
                                                Wald chi2(28)     =     164.44
                                                Prob > chi2       =     0.0000
Log pseudolikelihood = -1010.1095               Pseudo R2         =     0.1185

----------------------------------------------------------------------------------
                 |               Robust
         ONTvote |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----------------+----------------------------------------------------------------
1                |  (base outcome)
-----------------+----------------------------------------------------------------
2                |
        1.female |  -.2763175   .1731394    -1.60   0.111    -.6156645    .0630295
         1.older |   .1096635   .2045872     0.54   0.592      -.29132     .510647
        1.lowinc |  -.0516736   .1918196    -0.27   0.788    -.4276331    .3242859
 1.missingincome |   .2531721   .3151972     0.80   0.422    -.3646031    .8709472
      1.HSorless |   .4076827    .235085     1.73   0.083    -.0530755    .8684409
    1.university |  -.5517702   .1788537    -3.09   0.002    -.9023171   -.2012233
        1.French |  -1.272773   .6386046    -1.99   0.046    -2.524416   -.0211313
       1.visible |  -.5558069   .2601702    -2.14   0.033    -1.065731   -.0458827
      1.catholic |  -.3325206   .2180835    -1.52   0.127    -.7599563    .0949151
    1.noreligion |  -.6898241   .2110804    -3.27   0.001    -1.103534   -.2761141
       1.working |    .320012   .2067061     1.55   0.122    -.0851245    .7251486
         1.union |  -.2451032   .2176527    -1.13   0.260    -.6716947    .1814883
       1.bigcity |  -.5308316   .1811395    -2.93   0.003    -.8858585   -.1758047
antiredistribute |   .2632946   .0347636     7.57   0.000     .1951592    .3314299
           _cons |  -.8144702   .3466652    -2.35   0.019    -1.493921    -.135019
-----------------+----------------------------------------------------------------
3                |
        1.female |   .1578504   .2010602     0.79   0.432    -.2362203    .5519211
         1.older |  -.7585452   .2435995    -3.11   0.002    -1.235992   -.2810989
```

1.lowinc	.4844278	.2252127	2.15	0.031	.0430191	.9258365
1.missingincome	.1635709	.365206	0.45	0.654	-.5522197	.8793615
1.HSorless	.8135454	.2447085	3.32	0.001	.3339255	1.293165
1.university	.0670251	.1994851	0.34	0.737	-.3239586	.4580088
1.French	.3026279	.4724237	0.64	0.522	-.6233055	1.228561
1.visible	-.6147069	.2967677	-2.07	0.038	-1.196361	-.0330529
1.catholic	-.0208322	.2628548	-0.08	0.937	-.5360182	.4943538
1.noreligion	.1635982	.2225306	0.74	0.462	-.2725539	.5997502
1.working	-.6422439	.2384732	-2.69	0.007	-1.109643	-.174845
1.union	.6338374	.2340321	2.71	0.007	.1751429	1.092532
1.bigcity	.1918818	.2009547	0.95	0.340	-.2019821	.5857458
antiredistribute	.0150056	.0387687	0.39	0.699	-.0609798	.0909909
_cons	-1.379383	.373849	-3.69	0.000	-2.112114	-.6466528

```
30 . mlogit ONTvote i.female i.older i.lowinc i.missingincome i.HSorless i.university
   >  i.French i.visible i.catholic i.noreligion i.working i.union i.bigcity antiredi
   > stribute if Province==35  [iweight=regionWT], baseoutcome(2) robust

   Iteration 0:   log pseudolikelihood =  -1145.875
   Iteration 1:   log pseudolikelihood = -1012.6823
   Iteration 2:   log pseudolikelihood = -1010.1127
   Iteration 3:   log pseudolikelihood = -1010.1095
   Iteration 4:   log pseudolikelihood = -1010.1095

   Multinomial logistic regression                 Number of obs     =      1,144
                                                   Wald chi2(28)     =     164.44
                                                   Prob > chi2       =     0.0000
   Log pseudolikelihood = -1010.1095               Pseudo R2         =     0.1185
```

ONTvote	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
1						
1.female	.2763175	.1731394	1.60	0.111	-.0630295	.6156645
1.older	-.1096635	.2045872	-0.54	0.592	-.510647	.29132
1.lowinc	.0516736	.1918196	0.27	0.788	-.3242859	.4276331
1.missingincome	-.2531721	.3151972	-0.80	0.422	-.8709472	.3646031
1.HSorless	-.4076827	.235085	-1.73	0.083	-.8684409	.0530755
1.university	.5517702	.1788537	3.09	0.002	.2012233	.9023171
1.French	1.272773	.6386046	1.99	0.046	.0211313	2.524416
1.visible	.5558069	.2601702	2.14	0.033	.0458827	1.065731
1.catholic	.3325206	.2180835	1.52	0.127	-.0949151	.7599563
1.noreligion	.6898241	.2110804	3.27	0.001	.2761141	1.103534
1.working	-.320012	.2067061	-1.55	0.122	-.7251486	.0851245
1.union	.2451032	.2176527	1.13	0.260	-.1814883	.6716947
1.bigcity	.5308316	.1811395	2.93	0.003	.1758047	.8858585
antiredistribute	-.2632946	.0347636	-7.57	0.000	-.3314299	-.1951592

_cons	.8144702	.3466652	2.35	0.019	.135019	1.493921
2	(base outcome)					
3						
1.female	.4341679	.2226722	1.95	0.051	-.0022615	.8705974
1.older	-.8682088	.2686544	-3.23	0.001	-1.394762	-.3416559
1.lowinc	.5361014	.246668	2.17	0.030	.0526411	1.019562
1.missingincome	-.0896011	.4205473	-0.21	0.831	-.9138587	.7346564
1.HSorless	.4058627	.2630279	1.54	0.123	-.1096624	.9213879
1.university	.6187953	.2193586	2.82	0.005	.1888604	1.04873
1.French	1.575401	.7085378	2.22	0.026	.1866927	2.96411
1.visible	-.0589	.3166119	-0.19	0.852	-.679448	.561648
1.catholic	.3116884	.2870907	1.09	0.278	-.250999	.8743758
1.noreligion	.8534222	.2598144	3.28	0.001	.3441954	1.362649
1.working	-.9622559	.2634728	-3.65	0.000	-1.478653	-.4458586
1.union	.8789406	.2574596	3.41	0.001	.374329	1.383552
1.bigcity	.7227134	.22331	3.24	0.001	.2850339	1.160393
antiredistribute	-.248289	.0440245	-5.64	0.000	-.3345754	-.1620026
_cons	-.5649132	.4209166	-1.34	0.180	-1.389895	.2600682

```
31 . mlogit ONTvote i.female i.older i.lowinc i.missingincome i.HSorless i.university
   >  i.French i.visible i.catholic i.noreligion i.working i.union i.bigcity antiredi
   > stribute if Province==35  [iweight=regionWT], baseoutcome(3) robust

   Iteration 0:   log pseudolikelihood =  -1145.875
   Iteration 1:   log pseudolikelihood = -1012.6823
   Iteration 2:   log pseudolikelihood = -1010.1127
   Iteration 3:   log pseudolikelihood = -1010.1095
   Iteration 4:   log pseudolikelihood = -1010.1095

   Multinomial logistic regression                 Number of obs     =      1,144
                                                   Wald chi2(28)     =     164.44
                                                   Prob > chi2       =     0.0000
   Log pseudolikelihood = -1010.1095               Pseudo R2         =     0.1185
```

ONTvote	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
1						
1.female	-.1578504	.2010602	-0.79	0.432	-.5519211	.2362203
1.older	.7585452	.2435995	3.11	0.002	.2810989	1.235992
1.lowinc	-.4844278	.2252127	-2.15	0.031	-.9258365	-.0430191
1.missingincome	-.1635709	.365206	-0.45	0.654	-.8793615	.5522197
1.HSorless	-.8135454	.2447085	-3.32	0.001	-1.293165	-.3339255
1.university	-.0670251	.1994851	-0.34	0.737	-.4580088	.3239586
1.French	-.3026279	.4724237	-0.64	0.522	-1.228561	.6233055

1.visible	.6147069	.2967677	2.07	0.038	.0330529	1.196361
1.catholic	.0208322	.2628548	0.08	0.937	-.4943538	.5360182
1.noreligion	-.1635982	.2225306	-0.74	0.462	-.5997502	.2725539
1.working	.6422439	.2384732	2.69	0.007	.174845	1.109643
1.union	-.6338374	.2340321	-2.71	0.007	-1.092532	-.1751429
1.bigcity	-.1918818	.2009547	-0.95	0.340	-.5857458	.2019821
antiredistribute	-.0150056	.0387687	-0.39	0.699	-.0909909	.0609798
_cons	1.379383	.373849	3.69	0.000	.6466528	2.112114
2						
1.female	-.4341679	.2226722	-1.95	0.051	-.8705974	.0022615
1.older	.8682088	.2686544	3.23	0.001	.3416559	1.394762
1.lowinc	-.5361014	.246668	-2.17	0.030	-1.019562	-.0526411
1.missingincome	.0896011	.4205473	0.21	0.831	-.7346564	.9138587
1.HSorless	-.4058627	.2630279	-1.54	0.123	-.9213879	.1096624
1.university	-.6187953	.2193586	-2.82	0.005	-1.04873	-.1888604
1.French	-1.575401	.7085378	-2.22	0.026	-2.96411	-.1866927
1.visible	.0589	.3166119	0.19	0.852	-.561648	.679448
1.catholic	-.3116884	.2870907	-1.09	0.278	-.8743758	.250999
1.noreligion	-.8534222	.2598144	-3.28	0.001	-1.362649	-.3441954
1.working	.9622559	.2634728	3.65	0.000	.4458586	1.478653
1.union	-.8789406	.2574596	-3.41	0.001	-1.383552	-.374329
1.bigcity	-.7227134	.22331	-3.24	0.001	-1.160393	-.2850339
antiredistribute	.248289	.0440245	5.64	0.000	.1620026	.3345754
_cons	.5649132	.4209166	1.34	0.180	-.2600682	1.389895
3	(base outcome)					

```
32 .
33 . margins, at(antiredistribute=(0 (1) 10))

   Predictive margins                              Number of obs     =      1,144
   Model VCE     : Robust

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

   1._at         : antiredist~e    =           0

   2._at         : antiredist~e    =           1

   3._at         : antiredist~e    =           2

   4._at         : antiredist~e    =           3

   5._at         : antiredist~e    =           4
```

```
6._at        : antiredist~e    =           5

7._at        : antiredist~e    =           6

8._at        : antiredist~e    =           7

9._at        : antiredist~e    =           8

10._at       : antiredist~e    =           9

11._at       : antiredist~e    =          10
```

	Margin	Delta-method Std. Err.	z	P>|z|	[95% Conf.	Interval]
_predict#_at						
1 1	.6192448	.0299956	20.64	0.000	.5604546	.6780351
1 2	.5894363	.0256937	22.94	0.000	.5390775	.6397951
1 3	.5558651	.0219026	25.38	0.000	.5129369	.5987933
1 4	.5187812	.0190103	27.29	0.000	.4815217	.5560407
1 5	.4786818	.0176436	27.13	0.000	.4441009	.5132627
1 6	.4363008	.0182739	23.88	0.000	.4004846	.4721169
1 7	.392564	.0206364	19.02	0.000	.3521175	.4330105
1 8	.3485165	.0238984	14.58	0.000	.3016766	.3953564
1 9	.3052313	.0272313	11.21	0.000	.2518589	.3586038
1 10	.2637167	.0300397	8.78	0.000	.2048399	.3225935
1 11	.2248344	.0319604	7.03	0.000	.1621932	.2874756
2 1	.1667934	.0228507	7.30	0.000	.1220068	.21158
2 2	.203612	.0220806	9.22	0.000	.1603349	.2468891
2 3	.2457398	.0205176	11.98	0.000	.2055262	.2859535
2 4	.2929166	.0186113	15.74	0.000	.2564391	.3293942
2 5	.3445464	.0173549	19.85	0.000	.3105315	.3785614
2 6	.3997036	.0180443	22.15	0.000	.3643374	.4350698
2 7	.4571849	.021145	21.62	0.000	.4157414	.4986284
2 8	.5156018	.0258267	19.96	0.000	.4649825	.5662211
2 9	.5734996	.0309156	18.55	0.000	.5129061	.6340931
2 10	.6294833	.0355038	17.73	0.000	.5598971	.6990695
2 11	.6823311	.0390077	17.49	0.000	.6058773	.7587848
3 1	.2139618	.0238789	8.96	0.000	.16716	.2607635
3 2	.2069517	.019074	10.85	0.000	.1695674	.2443359
3 3	.198395	.0152809	12.98	0.000	.1684451	.228345
3 4	.1883021	.0130183	14.46	0.000	.1627868	.2138175
3 5	.1767717	.0126239	14.00	0.000	.1520294	.2015141
3 6	.1639956	.013749	11.93	0.000	.137048	.1909433
3 7	.1502511	.0156059	9.63	0.000	.1196642	.180838
3 8	.1358817	.0175546	7.74	0.000	.1014754	.170288
3 9	.1212691	.0192248	6.31	0.000	.0835891	.158949
3 10	.1068	.0204248	5.23	0.000	.0667681	.146832

3 11	.0928345	.0210696	4.41	0.000	.0515388	.1341303

```
34 . marginsplot, recast(line) recastci(rarea) saving(ONTleftright)

  Variables that uniquely identify margins: antiredistribute _outcome
(file ONTleftright.gph saved)

35 .
36 . *** Party identification
37 .
38 . mlogit ONTvote i.female i.older i.lowinc i.missingincome i.HSorless i.university
>  i.French i.visible i.catholic i.noreligion i.working i.union i.bigcity antiredi
> stribute IDliberal IDconservative IDndp if Province==35  [iweight=regionWT], rob
> ust

Iteration 0:   log pseudolikelihood =  -1145.875
Iteration 1:   log pseudolikelihood = -803.03948
Iteration 2:   log pseudolikelihood = -783.69986
Iteration 3:   log pseudolikelihood = -764.43554
Iteration 4:   log pseudolikelihood = -763.94886
Iteration 5:   log pseudolikelihood = -763.92082
Iteration 6:   log pseudolikelihood = -763.91434
Iteration 7:   log pseudolikelihood = -763.91298
Iteration 8:   log pseudolikelihood = -763.91274
Iteration 9:   log pseudolikelihood = -763.91271

Multinomial logistic regression                 Number of obs     =      1,144
                                                Wald chi2(34)     =    4699.68
                                                Prob > chi2       =     0.0000
Log pseudolikelihood = -763.91271               Pseudo R2         =     0.3333
```

ONTvote	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
1	(base outcome)					
2						
1.female	-.2296344	.213635	-1.07	0.282	-.6483513	.1890824
1.older	.0131482	.2564564	0.05	0.959	-.4894972	.5157936
1.lowinc	-.2267972	.2487231	-0.91	0.362	-.7142854	.2606911
1.missingincome	.3334016	.3514751	0.95	0.343	-.3554769	1.02228
1.HSorless	.127839	.2738353	0.47	0.641	-.4088684	.6645464
1.university	-.7880499	.2270525	-3.47	0.001	-1.233065	-.3430352
1.French	-1.494822	.7274404	-2.05	0.040	-2.920579	-.0690655
1.visible	-.549506	.3017094	-1.82	0.069	-1.140846	.0418336
1.catholic	-.350634	.267188	-1.31	0.189	-.8743128	.1730448
1.noreligion	-.540866	.2535889	-2.13	0.033	-1.037891	-.0438408

1.working	.2133177	.2574232	0.83	0.407	-.2912225	.717858
1.union	-.10156	.2639619	-0.38	0.700	-.6189159	.4157958
1.bigcity	-.4101327	.2266708	-1.81	0.070	-.8543994	.034134
antiredistribute	.2015088	.0421327	4.78	0.000	.1189302	.2840873
IDliberal	-3.933423	.7258507	-5.42	0.000	-5.356064	-2.510782
IDconservative	3.539181	.3765524	9.40	0.000	2.801152	4.27721
IDndp	-14.67048	.3458909	-42.41	0.000	-15.34842	-13.99255
_cons	-.4527964	.4160371	-1.09	0.276	-1.268214	.3626213
3						
1.female	.1523686	.2226614	0.68	0.494	-.2840397	.5887769
1.older	-.991129	.2678828	-3.70	0.000	-1.51617	-.4660884
1.lowinc	.3188625	.2527978	1.26	0.207	-.1766121	.8143372
1.missingincome	.308911	.3892854	0.79	0.427	-.4540743	1.071896
1.HSorless	.6546049	.2734365	2.39	0.017	.1186792	1.190531
1.university	-.3244032	.2288144	-1.42	0.156	-.7728712	.1240648
1.French	.4716031	.6397168	0.74	0.461	-.7822188	1.725425
1.visible	-.565606	.3090671	-1.83	0.067	-1.171366	.0401545
1.catholic	.1114528	.2805587	0.40	0.691	-.4384322	.6613378
1.noreligion	-.0799549	.2495898	-0.32	0.749	-.5691419	.4092321
1.working	-.65533	.2588334	-2.53	0.011	-1.162634	-.1480259
1.union	.6012438	.2631495	2.28	0.022	.0854802	1.117007
1.bigcity	.2229203	.2263888	0.98	0.325	-.2207935	.6666342
antiredistribute	.0107554	.0438095	0.25	0.806	-.0751096	.0966204
IDliberal	-2.808996	.4562316	-6.16	0.000	-3.703193	-1.914798
IDconservative	.3289456	.7018692	0.47	0.639	-1.046693	1.704584
IDndp	1.873991	.3552732	5.27	0.000	1.177668	2.570314
_cons	-.8801526	.4193354	-2.10	0.036	-1.702035	-.0582703

```
39 . mlogit ONTvote i.female i.older i.lowinc i.missingincome i.HSorless i.university
   >  i.French i.visible i.catholic i.noreligion i.working i.union i.bigcity antiredi
   > stribute IDliberal IDconservative IDndp if Province==35  [iweight=regionWT], bas
   > eoutcome(2) robust

   Iteration 0:   log pseudolikelihood =  -1145.875
   Iteration 1:   log pseudolikelihood = -803.03948
   Iteration 2:   log pseudolikelihood = -783.69986
   Iteration 3:   log pseudolikelihood = -764.43554
   Iteration 4:   log pseudolikelihood = -763.94886
   Iteration 5:   log pseudolikelihood = -763.92082
   Iteration 6:   log pseudolikelihood = -763.91434
   Iteration 7:   log pseudolikelihood = -763.91298
   Iteration 8:   log pseudolikelihood = -763.91274
   Iteration 9:   log pseudolikelihood = -763.91271

   Multinomial logistic regression                 Number of obs     =      1,144
                                                   Wald chi2(34)     =    4640.11
                                                   Prob > chi2       =     0.0000
```

Log pseudolikelihood = **-763.91271** Pseudo R2 = **0.3333**

ONTvote	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
1						
1.female	.2296344	.213635	1.07	0.282	-.1890824	.6483513
1.older	-.0131482	.2564564	-0.05	0.959	-.5157936	.4894972
1.lowinc	.2267972	.2487231	0.91	0.362	-.2606911	.7142854
1.missingincome	-.3334016	.3514751	-0.95	0.343	-1.02228	.3554769
1.HSorless	-.127839	.2738353	-0.47	0.641	-.6645464	.4088684
1.university	.7880499	.2270525	3.47	0.001	.3430352	1.233065
1.French	1.494822	.7274404	2.05	0.040	.0690655	2.920579
1.visible	.549506	.3017094	1.82	0.069	-.0418336	1.140846
1.catholic	.350634	.267188	1.31	0.189	-.1730448	.8743128
1.noreligion	.540866	.2535889	2.13	0.033	.0438408	1.037891
1.working	-.2133177	.2574232	-0.83	0.407	-.717858	.2912225
1.union	.10156	.2639619	0.38	0.700	-.4157958	.6189159
1.bigcity	.4101327	.2266708	1.81	0.070	-.034134	.8543994
antiredistribute	-.2015088	.0421327	-4.78	0.000	-.2840873	-.1189302
IDliberal	3.933423	.7258507	5.42	0.000	2.510782	5.356064
IDconservative	-3.539181	.3765524	-9.40	0.000	-4.27721	-2.801152
IDndp	14.67048	.3471047	42.27	0.000	13.99017	15.35079
_cons	.4527964	.4160371	1.09	0.276	-.3626213	1.268214
2	(base outcome)					
3						
1.female	.382003	.2564206	1.49	0.136	-.1205721	.8845781
1.older	-1.004277	.3135842	-3.20	0.001	-1.618891	-.3896636
1.lowinc	.5456597	.3075729	1.77	0.076	-.0571721	1.148492
1.missingincome	-.0244906	.4465211	-0.05	0.956	-.8996558	.8506746
1.HSorless	.5267659	.2998838	1.76	0.079	-.0609956	1.114527
1.university	.4636467	.2679743	1.73	0.084	-.0615732	.9888667
1.French	1.966426	.798412	2.46	0.014	.4015667	3.531284
1.visible	-.0161	.3434138	-0.05	0.963	-.6891786	.6569786
1.catholic	.4620868	.3149146	1.47	0.142	-.1551345	1.079308
1.noreligion	.4609111	.301184	1.53	0.126	-.1293987	1.051221
1.working	-.8686478	.3075685	-2.82	0.005	-1.471471	-.2658245
1.union	.7028039	.2964823	2.37	0.018	.1217093	1.283898
1.bigcity	.633053	.2680883	2.36	0.018	.1076097	1.158496
antiredistribute	-.1907534	.0505867	-3.77	0.000	-.2899015	-.0916052
IDliberal	1.124427	.8410191	1.34	0.181	-.5239399	2.772795
IDconservative	-3.210236	.6413888	-5.01	0.000	-4.467335	-1.953137
IDndp	16.54447	.2969344	55.72	0.000	15.96249	17.12645
_cons	-.4273562	.4869388	-0.88	0.380	-1.381739	.5270263

```
40 .
41 . margins, dydx(IDliberal)

   Average marginal effects                        Number of obs     =      1,144
   Model VCE     : Robust

   dy/dx w.r.t. : IDliberal
   1._predict    : Pr(ONTvote==1), predict(pr outcome(1))
   2._predict    : Pr(ONTvote==2), predict(pr outcome(2))
   3._predict    : Pr(ONTvote==3), predict(pr outcome(3))
```

	dy/dx	Delta-method Std. Err.	z	P>|z|	[95% Conf.	Interval]
IDliberal						
_predict						
1	.5657068	.0711948	7.95	0.000	.4261675	.7052461
2	-.4034691	.0935344	-4.31	0.000	-.5867931	-.2201451
3	-.1622377	.0552538	-2.94	0.003	-.2705331	-.0539423

```
42 . margins, dydx(IDconservative)

   Average marginal effects                        Number of obs     =      1,144
   Model VCE     : Robust

   dy/dx w.r.t. : IDconservative
   1._predict    : Pr(ONTvote==1), predict(pr outcome(1))
   2._predict    : Pr(ONTvote==2), predict(pr outcome(2))
   3._predict    : Pr(ONTvote==3), predict(pr outcome(3))
```

	dy/dx	Delta-method Std. Err.	z	P>|z|	[95% Conf.	Interval]
IDconservative						
_predict						
1	-.3489682	.0706415	-4.94	0.000	-.4874231	-.2105133
2	.4456201	.0371331	12.00	0.000	.3728405	.5183997
3	-.0966519	.0691601	-1.40	0.162	-.2322031	.0388994

```
43 . margins, dydx(IDndp)

   Average marginal effects                        Number of obs     =      1,144
   Model VCE     : Robust

   dy/dx w.r.t. : IDndp
```

```
1._predict   : Pr(ONTvote==1), predict(pr outcome(1))
2._predict   : Pr(ONTvote==2), predict(pr outcome(2))
3._predict   : Pr(ONTvote==3), predict(pr outcome(3))
```

	dy/dx	Delta-method Std. Err.	z	P>|z|	[95% Conf.	Interval]
IDndp						
_predict						
1	**1.210857**	**.0888827**	**13.62**	**0.000**	**1.03665**	**1.385064**
2	**-1.96879**	**.1007284**	**-19.55**	**0.000**	**-2.166214**	**-1.771366**
3	**.7579328**	**.0651379**	**11.64**	**0.000**	**.630265**	**.8856007**

```
44 .
45 . tab ONTvote IDliberal if Province==35 [aweight=regionWT], col
```

Key
frequency *column percentage*

ONTvote	IDliberal 0	1	Total
1	**376.1854** **37.21**	**179.57919** **96.51**	**555.76459** **46.43**
2	**433.38061** **42.87**	**2.0262033** **1.09**	**435.40681** **36.37**
3	**201.35736** **19.92**	**4.4712421** **2.40**	**205.8286** **17.20**
Total	**1,010.923** **100.00**	**186.07664** **100.00**	**1,197** **100.00**

```
46 . tab ONTvote IDconservative if Province==35 [aweight=regionWT], col
```

Key
frequency *column percentage*

ONTvote	IDconservative 0	1	Total
1	**548.80715**	**6.9574368**	**555.76459**
	55.15	**3.45**	**46.43**
2	**244.68609**	**190.72073**	**435.40681**
	24.59	**94.44**	**36.37**
3	**201.56393**	**4.2646663**	**205.8286**
	20.26	**2.11**	**17.20**
Total	**995.05717**	**201.94283**	**1,197**
	100.00	**100.00**	**100.00**

```
47 . tab ONTvote IDndp if Province==35 [aweight=regionWT], col
```

Key
frequency
column percentage

ONTvote	IDndp 0	1	Total
1	**532.59396**	**23.170622**	**555.76459**
	47.34	**32.20**	**46.43**
2	**435.40681**	**0**	**435.40681**
	38.70	**0.00**	**36.37**
3	**157.0421**	**48.7865**	**205.8286**
	13.96	**67.80**	**17.20**
Total	**1,125.043**	**71.957122**	**1,197**
	100.00	**100.00**	**100.00**

```
48 .
49 . tab ONTvote IDnone if Province==35 [aweight=regionWT], col
```

Key
frequency

column percentage

ONTvote	IDnone 0	1	Total
1	**209.70725**	**346.05734**	**555.76459**
	45.59	**46.95**	**46.43**
2	**192.74693**	**242.659882**	**435.40681**
	41.90	**32.92**	**36.37**
3	**57.5224084**	**148.30619**	**205.8286**
	12.51	**20.12**	**17.20**
Total	**459.97659**	**737.02341**	**1,197**
	100.00	**100.00**	**100.00**

```
50 .
51 . logit LIBvote i.female i.older i.lowinc i.missingincome i.HSorless i.university
   > i.French i.visible i.catholic i.noreligion i.working i.union i.bigcity antiredis
   > tribute IDliberal IDconservative IDndp if Province==35  [iweight=regionWT], robu
   > st

   Iteration 0:   log pseudolikelihood = -796.18216
   Iteration 1:   log pseudolikelihood = -572.39094
   Iteration 2:   log pseudolikelihood = -569.20699
   Iteration 3:   log pseudolikelihood = -569.18266
   Iteration 4:   log pseudolikelihood = -569.18266

   Logistic regression                             Number of obs     =      1,201
                                                   Wald chi2(17)     =     226.81
                                                   Prob > chi2       =     0.0000
   Log pseudolikelihood = -569.18266               Pseudo R2         =     0.2851
```

LIBvote	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
1.female	**.0890022**	**.1700833**	**0.52**	**0.601**	**-.2443549**	**.4223593**
1.older	**.4436661**	**.1998706**	**2.22**	**0.026**	**.0519269**	**.8354054**
1.lowinc	**-.0722848**	**.1924102**	**-0.38**	**0.707**	**-.4494019**	**.3048324**
1.missingincome	**-.3505026**	**.2783884**	**-1.26**	**0.208**	**-.8961339**	**.1951287**
1.HSorless	**-.3003107**	**.2259024**	**-1.33**	**0.184**	**-.7430713**	**.1424499**
1.university	**.606701**	**.1785987**	**3.40**	**0.001**	**.256654**	**.956748**
1.French	**.040456**	**.5598823**	**0.07**	**0.942**	**-1.056893**	**1.137805**
1.visible	**.5208142**	**.2448012**	**2.13**	**0.033**	**.0410126**	**1.000616**
1.catholic	**.1757078**	**.2201589**	**0.80**	**0.425**	**-.2557957**	**.6072113**

1.noreligion	.3089335	.1935736	1.60	0.111	-.0704638	.6883307
1.working	.2182943	.1987477	1.10	0.272	-.171244	.6078326
1.union	-.3797758	.2054062	-1.85	0.064	-.7823647	.022813
1.bigcity	.0904949	.176811	0.51	0.609	-.2560483	.4370381
antiredistribute	-.1013346	.0333786	-3.04	0.002	-.1667555	-.0359137
IDliberal	3.383372	.3902866	8.67	0.000	2.618425	4.14832
IDconservative	-3.052665	.3799386	-8.03	0.000	-3.797331	-2.307999
IDndp	-.8919181	.3344635	-2.67	0.008	-1.547455	-.2363816
_cons	-.2991423	.3263985	-0.92	0.359	-.9388716	.3405871

```
52 .
53 . margins, dydx(IDliberal)

   Average marginal effects                        Number of obs     =      1,201
   Model VCE    : Robust

   Expression   : Pr(LIBvote), predict()
   dy/dx w.r.t. : IDliberal
```

	Delta-method dy/dx	Std. Err.	z	P>|z|	[95% Conf.	Interval]
IDliberal	.5667254	.0604391	9.38	0.000	.4482668	.6851839

```
54 . margins, dydx(IDconservative)

   Average marginal effects                        Number of obs     =      1,201
   Model VCE    : Robust

   Expression   : Pr(LIBvote), predict()
   dy/dx w.r.t. : IDconservative
```

	Delta-method dy/dx	Std. Err.	z	P>|z|	[95% Conf.	Interval]
IDconservative	-.5113309	.0615581	-8.31	0.000	-.6319825	-.3906793

```
55 . margins, dydx(IDndp)

   Average marginal effects                        Number of obs     =      1,201
   Model VCE    : Robust

   Expression   : Pr(LIBvote), predict()
   dy/dx w.r.t. : IDndp
```

	Delta-method dy/dx	Std. Err.	z	P>|z|	[95% Conf.	Interval]
IDndp	-.1493991	.0549088	-2.72	0.007	-.2570184	-.0417797

```
56 .
57 . logit CPCvote i.female i.older i.lowinc i.missingincome i.HSorless i.university
   > i.French i.visible i.catholic i.noreligion i.working i.union i.bigcity antiredis
   > tribute IDliberal IDconservative IDndp if Province==35  [iweight=regionWT], robu
   > st

   note: IDndp != 0 predicts failure perfectly
         IDndp dropped and 97 obs not used

   Iteration 0:   log pseudolikelihood =  -716.2156
   Iteration 1:   log pseudolikelihood = -462.83695
   Iteration 2:   log pseudolikelihood =  -456.4663
   Iteration 3:   log pseudolikelihood = -453.88802
   Iteration 4:   log pseudolikelihood = -453.86348
   Iteration 5:   log pseudolikelihood = -453.86346

   Logistic regression                             Number of obs     =      1,104
                                                   Wald chi2(16)     =     191.17
                                                   Prob > chi2       =     0.0000
   Log pseudolikelihood = -453.86346               Pseudo R2         =     0.3663
```

CPCvote	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
1.female	-.2548256	.1995299	-1.28	0.202	-.6458971	.1362459
1.older	.3247149	.2407644	1.35	0.177	-.1471747	.7966044
1.lowinc	-.3584684	.2359257	-1.52	0.129	-.8208742	.1039374
1.missingincome	.2381719	.3306576	0.72	0.471	-.4099052	.8862489
1.HSorless	-.0557363	.2445329	-0.23	0.820	-.535012	.4235394
1.university	-.6995505	.2137734	-3.27	0.001	-1.118539	-.2805623
1.French	-1.731564	.6404923	-2.70	0.007	-2.986906	-.4762223
1.visible	-.4137319	.2801541	-1.48	0.140	-.962824	.1353601
1.catholic	-.3697327	.2461307	-1.50	0.133	-.8521401	.1126747
1.noreligion	-.5062119	.2385955	-2.12	0.034	-.9738505	-.0385733
1.working	.4084926	.2385325	1.71	0.087	-.0590226	.8760077
1.union	-.3953349	.2386459	-1.66	0.098	-.8630722	.0724024
1.bigcity	-.4729981	.2133226	-2.22	0.027	-.8911028	-.0548934
antiredistribute	.1986757	.038908	5.11	0.000	.1224174	.274934
IDliberal	-3.613385	.7280294	-4.96	0.000	-5.040297	-2.186474
IDconservative	3.412969	.3291732	10.37	0.000	2.767801	4.058137

IDndp	**0**	(omitted)				
_cons	**-.9017304**	**.3843846**	**-2.35**	**0.019**	**-1.65511**	**-.1483505**

```
58 .
59 . margins, dydx(IDliberal)

Average marginal effects                        Number of obs     =      1,104
Model VCE    : Robust

Expression   : Pr(CPCvote), predict()
dy/dx w.r.t. : IDliberal
```

	dy/dx	Delta-method Std. Err.	z	P>|z|	[95% Conf.	Interval]
IDliberal	**-.4933742**	**.0990986**	**-4.98**	**0.000**	**-.6876038**	**-.2991445**

```
60 . margins, dydx(IDconservative)

Average marginal effects                        Number of obs     =      1,104
Model VCE    : Robust

Expression   : Pr(CPCvote), predict()
dy/dx w.r.t. : IDconservative
```

	dy/dx	Delta-method Std. Err.	z	P>|z|	[95% Conf.	Interval]
IDconservative	**.4660092**	**.0369747**	**12.60**	**0.000**	**.3935401**	**.5384783**

```
61 . margins, dydx(IDndp)

Average marginal effects                        Number of obs     =      1,104
Model VCE    : Robust

Expression   : Pr(CPCvote), predict()
dy/dx w.r.t. : IDndp
```

	dy/dx	Delta-method Std. Err.	z	P>|z|	[95% Conf.	Interval]
IDndp	**0**	(omitted)				

```
62 .
63 . logit NDPvote i.female i.older i.lowinc i.missingincome i.HSorless i.university
   > i.French i.visible i.catholic i.noreligion i.working i.union i.bigcity antiredis
   > tribute IDliberal IDconservative IDndp if Province==35  [iweight=regionWT], robu
   > st

   Iteration 0:   log pseudolikelihood =  -523.2759
   Iteration 1:   log pseudolikelihood = -429.53165
   Iteration 2:   log pseudolikelihood = -411.72508
   Iteration 3:   log pseudolikelihood = -408.23385
   Iteration 4:   log pseudolikelihood = -408.20408
   Iteration 5:   log pseudolikelihood = -408.20405

   Logistic regression                             Number of obs     =      1,201
                                                   Wald chi2(17)     =     125.50
                                                   Prob > chi2       =     0.0000
   Log pseudolikelihood = -408.20405               Pseudo R2         =     0.2199
```

NDPvote	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
1.female	.2392534	.2064904	1.16	0.247	-.1654604	.6439672
1.older	-.9092802	.2468861	-3.68	0.000	-1.393168	-.4253923
1.lowinc	.2914472	.2379661	1.22	0.221	-.1749578	.7578522
1.missingincome	.1012925	.378237	0.27	0.789	-.6400385	.8426234
1.HSorless	.5937435	.243006	2.44	0.015	.1174604	1.070027
1.university	-.0798475	.2111247	-0.38	0.705	-.4936444	.3339494
1.French	.7463728	.5976397	1.25	0.212	-.4249795	1.917725
1.visible	-.3804715	.2876808	-1.32	0.186	-.9443155	.1833725
1.catholic	.2596998	.256999	1.01	0.312	-.244009	.7634086
1.noreligion	.058526	.2329176	0.25	0.802	-.397984	.5150361
1.working	-.6788295	.234737	-2.89	0.004	-1.138905	-.2187535
1.union	.4279929	.235271	1.82	0.069	-.0331299	.8891157
1.bigcity	.3175153	.2126708	1.49	0.135	-.0993118	.7343425
antiredistribute	-.0430197	.0391582	-1.10	0.272	-.1197683	.033729
IDliberal	-2.314432	.4626743	-5.00	0.000	-3.221256	-1.407607
IDconservative	-2.301903	.6004163	-3.83	0.000	-3.478697	-1.125109
IDndp	2.314443	.3444779	6.72	0.000	1.639279	2.989608
_cons	-1.469537	.3860867	-3.81	0.000	-2.226253	-.7128214

```
64 .
65 . margins, dydx(IDliberal)

   Average marginal effects                        Number of obs     =      1,201
   Model VCE    : Robust
```

```
Expression    : Pr(NDPvote), predict()
dy/dx w.r.t. : IDliberal
```

	dy/dx	Delta-method Std. Err.	z	P>|z|	[95% Conf.	Interval]
IDliberal	-.2536904	.0514721	-4.93	0.000	-.3545738	-.1528069

```
66 . margins, dydx(IDconservative)

   Average marginal effects                    Number of obs     =      1,201
   Model VCE    : Robust

   Expression   : Pr(NDPvote), predict()
   dy/dx w.r.t. : IDconservative
```

	dy/dx	Delta-method Std. Err.	z	P>|z|	[95% Conf.	Interval]
IDconservative	-.2523171	.0653072	-3.86	0.000	-.3803169	-.1243173

```
67 . margins, dydx(IDndp)

   Average marginal effects                    Number of obs     =      1,201
   Model VCE    : Robust

   Expression   : Pr(NDPvote), predict()
   dy/dx w.r.t. : IDndp
```

	dy/dx	Delta-method Std. Err.	z	P>|z|	[95% Conf.	Interval]
IDndp	.2536917	.0339584	7.47	0.000	.1871345	.3202488

```
68 .
69 . *** Issues
70 .
71 . mlogit ONTvote i.female i.older i.lowinc i.missingincome i.HSorless i.university
   >  i.French i.visible i.catholic i.noreligion i.working i.union i.bigcity antiredi
   > stribute IDliberal IDconservative IDndp sociotropic budget i.antiniqab rehabilit
   > ate fewerimmigrants corruption if Province==35  [iweight=regionWT], robust

   Iteration 0:   log pseudolikelihood =  -1145.875
```

```
Iteration 1:   log pseudolikelihood = -721.74503
Iteration 2:   log pseudolikelihood = -680.43645
Iteration 3:   log pseudolikelihood = -666.92164
Iteration 4:   log pseudolikelihood =  -666.2703
Iteration 5:   log pseudolikelihood = -666.22523
Iteration 6:   log pseudolikelihood = -666.21612
Iteration 7:   log pseudolikelihood = -666.21396
Iteration 8:   log pseudolikelihood = -666.21357
Iteration 9:   log pseudolikelihood = -666.21353
Iteration 10:  log pseudolikelihood = -666.21352

Multinomial logistic regression                 Number of obs     =      1,144
                                                Wald chi2(46)     =    2862.66
                                                Prob > chi2       =     0.0000
Log pseudolikelihood = -666.21352               Pseudo R2         =     0.4186
```

ONTvote	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
1	(base outcome)					
2						
1.female	-.0851094	.2518015	-0.34	0.735	-.5786313	.4084125
1.older	.0969398	.2851269	0.34	0.734	-.4618986	.6557782
1.lowinc	-.0754704	.2827348	-0.27	0.790	-.6296205	.4786797
1.missingincome	.2027574	.4647707	0.44	0.663	-.7081765	1.113691
1.HSorless	-.1141924	.3152957	-0.36	0.717	-.7321606	.5037757
1.university	-.3697779	.2630361	-1.41	0.160	-.8853192	.1457635
1.French	-.9786618	.8162622	-1.20	0.231	-2.578506	.6211826
1.visible	-.913688	.3195975	-2.86	0.004	-1.540088	-.2872885
1.catholic	-.7143322	.2935782	-2.43	0.015	-1.289735	-.1389294
1.noreligion	-.4073986	.3032684	-1.34	0.179	-1.001794	.1869966
1.working	.2194447	.2928557	0.75	0.454	-.3545418	.7934312
1.union	-.129035	.2913713	-0.44	0.658	-.7001123	.4420423
1.bigcity	-.4185544	.2547483	-1.64	0.100	-.9178518	.080743
antiredistribute	.1682872	.0519394	3.24	0.001	.0664879	.2700866
IDliberal	-3.263721	.7170737	-4.55	0.000	-4.669159	-1.858282
IDconservative	2.798647	.4498287	6.22	0.000	1.916998	3.680295
IDndp	-15.44055	.5162673	-29.91	0.000	-16.45241	-14.42868
sociotropic	1.108039	.230805	4.80	0.000	.6556701	1.560409
budget	.658864	.1806633	3.65	0.000	.3047703	1.012958
1.antiniqab	.5401351	.2971551	1.82	0.069	-.0422781	1.122548
rehabilitate	-.172934	.0451813	-3.83	0.000	-.2614878	-.0843802
fewerimmigrants	.1204897	.0478901	2.52	0.012	.0266268	.2143527
corruption	-.6665296	.1578253	-4.22	0.000	-.9758614	-.3571977
_cons	-1.245113	.8423583	-1.48	0.139	-2.896105	.4058789
3						

1.female	.1505606	.2228409	0.68	0.499	-.2861994	.5873207
1.older	-.9287998	.278211	-3.34	0.001	-1.474083	-.3835163
1.lowinc	.2565943	.2589207	0.99	0.322	-.250881	.7640696
1.missingincome	.3441284	.3926669	0.88	0.381	-.4254846	1.113741
1.HSorless	.6485356	.2752013	2.36	0.018	.109151	1.18792
1.university	-.3160907	.2406879	-1.31	0.189	-.7878303	.1556489
1.French	.5160905	.6727538	0.77	0.443	-.8024828	1.834664
1.visible	-.6171653	.3168033	-1.95	0.051	-1.238088	.0037577
1.catholic	.0988354	.2779522	0.36	0.722	-.445941	.6436117
1.noreligion	-.0463715	.2549622	-0.18	0.856	-.5460881	.4533452
1.working	-.6276072	.2635182	-2.38	0.017	-1.144093	-.1111211
1.union	.5585255	.264177	2.11	0.034	.040748	1.076303
1.bigcity	.2105803	.2353777	0.89	0.371	-.2507516	.6719121
antiredistribute	-.0021218	.044949	-0.05	0.962	-.0902203	.0859767
IDliberal	-2.764311	.4643686	-5.95	0.000	-3.674457	-1.854166
IDconservative	.1547126	.7161347	0.22	0.829	-1.248886	1.558311
IDndp	1.871792	.3749631	4.99	0.000	1.136877	2.606706
sociotropic	.3551612	.2126933	1.67	0.095	-.06171	.7720325
budget	.2490618	.1217288	2.05	0.041	.0104778	.4876459
1.antiniqab	-.0230953	.2605994	-0.09	0.929	-.5338608	.4876703
rehabilitate	.0263331	.0371414	0.71	0.478	-.0464627	.0991289
fewerimmigrants	.020938	.0446536	0.47	0.639	-.0665814	.1084574
corruption	.0510571	.149463	0.34	0.733	-.241885	.3439993
_cons	-1.399184	.669511	-2.09	0.037	-2.711401	-.0869666

```
72 . mlogit ONTvote i.female i.older i.lowinc i.missingincome i.HSorless i.university
   >  i.French i.visible i.catholic i.noreligion i.working i.union i.bigcity antiredi
   > stribute IDliberal IDconservative IDndp sociotropic budget i.antiniqab rehabilit
   > ate fewerimmigrants corruption if Province==35  [iweight=regionWT], baseoutcome(
   > 2) robust

   Iteration 0:   log pseudolikelihood =  -1145.875
   Iteration 1:   log pseudolikelihood = -721.74503
   Iteration 2:   log pseudolikelihood = -680.43645
   Iteration 3:   log pseudolikelihood = -666.92164
   Iteration 4:   log pseudolikelihood =  -666.2703
   Iteration 5:   log pseudolikelihood = -666.22523
   Iteration 6:   log pseudolikelihood = -666.21612
   Iteration 7:   log pseudolikelihood = -666.21396
   Iteration 8:   log pseudolikelihood = -666.21357
   Iteration 9:   log pseudolikelihood = -666.21353
   Iteration 10:  log pseudolikelihood = -666.21352

   Multinomial logistic regression                 Number of obs     =      1,144
                                                   Wald chi2(46)     =    2963.69
                                                   Prob > chi2       =     0.0000
   Log pseudolikelihood = -666.21352               Pseudo R2         =     0.4186
```

ONTvote	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
1						
1.female	.0851094	.2518015	0.34	0.735	-.4084125	.5786313
1.older	-.0969398	.2851269	-0.34	0.734	-.6557782	.4618986
1.lowinc	.0754704	.2827348	0.27	0.790	-.4786797	.6296205
1.missingincome	-.2027574	.4647707	-0.44	0.663	-1.113691	.7081765
1.HSorless	.1141924	.3152957	0.36	0.717	-.5037757	.7321606
1.university	.3697779	.2630361	1.41	0.160	-.1457635	.8853192
1.French	.9786618	.8162622	1.20	0.231	-.6211826	2.578506
1.visible	.913688	.3195975	2.86	0.004	.2872885	1.540088
1.catholic	.7143322	.2935782	2.43	0.015	.1389294	1.289735
1.noreligion	.4073986	.3032684	1.34	0.179	-.1869966	1.001794
1.working	-.2194447	.2928557	-0.75	0.454	-.7934312	.3545418
1.union	.129035	.2913713	0.44	0.658	-.4420423	.7001123
1.bigcity	.4185544	.2547483	1.64	0.100	-.080743	.9178518
antiredistribute	-.1682872	.0519394	-3.24	0.001	-.2700866	-.0664879
IDliberal	3.263721	.7170737	4.55	0.000	1.858282	4.669159
IDconservative	-2.798647	.4498287	-6.22	0.000	-3.680295	-1.916998
IDndp	15.44055	.5147688	30.00	0.000	14.43162	16.44948
sociotropic	-1.108039	.230805	-4.80	0.000	-1.560409	-.6556701
budget	-.658864	.1806633	-3.65	0.000	-1.012958	-.3047703
1.antiniqab	-.5401351	.2971551	-1.82	0.069	-1.122548	.0422781
rehabilitate	.172934	.0451813	3.83	0.000	.0843802	.2614878
fewerimmigrants	-.1204897	.0478901	-2.52	0.012	-.2143527	-.0266268
corruption	.6665296	.1578253	4.22	0.000	.3571977	.9758614
_cons	1.245113	.8423583	1.48	0.139	-.4058789	2.896105
2	(base outcome)					
3						
1.female	.23567	.2893441	0.81	0.415	-.3314339	.8027739
1.older	-1.02574	.3428747	-2.99	0.003	-1.697762	-.3537176
1.lowinc	.3320647	.3552018	0.93	0.350	-.3641181	1.028247
1.missingincome	.141371	.5014272	0.28	0.778	-.8414082	1.12415
1.HSorless	.762728	.3432209	2.22	0.026	.0900275	1.435429
1.university	.0536871	.2980791	0.18	0.857	-.5305372	.6379115
1.French	1.494752	.8829432	1.69	0.090	-.2357845	3.225289
1.visible	.2965227	.3664463	0.81	0.418	-.4216988	1.014744
1.catholic	.8131676	.3478662	2.34	0.019	.1313624	1.494973
1.noreligion	.3610272	.3478166	1.04	0.299	-.3206809	1.042735
1.working	-.8470519	.3338085	-2.54	0.011	-1.501305	-.1927992
1.union	.6875605	.3281164	2.10	0.036	.0444642	1.330657
1.bigcity	.6291347	.2956814	2.13	0.033	.0496097	1.20866
antiredistribute	-.1704091	.056965	-2.99	0.003	-.2820585	-.0587596
IDliberal	.4994092	.8338903	0.60	0.549	-1.134986	2.133804
IDconservative	-2.643934	.6966059	-3.80	0.000	-4.009256	-1.278611

```
          IDndp |   17.31234   .3936179    43.98   0.000     16.54086    18.08382
    sociotropic |  -.7528783   .2667804    -2.82   0.005    -1.275758   -.2299982
         budget |  -.4098021   .1911341    -2.14   0.032    -.7844181   -.0351861
    1.antiniqab |  -.5632304   .3460681    -1.63   0.104    -1.241511    .1150506
  rehabilitate |   .1992671   .0498366     4.00   0.000     .1015891     .296945
fewerimmigrants |  -.0995517   .0559298    -1.78   0.075    -.2091721    .0100686
     corruption |   .7175867    .177541     4.04   0.000     .3696128    1.065561
          _cons |   -.154071   .8861082    -0.17   0.862    -1.890811    1.582669
------------------------------------------------------------------------------

 73 .
 74 . margins, at(sociotropic=(-1 0 1))

Predictive margins                              Number of obs     =      1,144
Model VCE    : Robust

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

1._at        : sociotropic     =          -1

2._at        : sociotropic     =           0

3._at        : sociotropic     =           1

------------------------------------------------------------------------------
             |            Delta-method
             |     Margin   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
_predict#_at |
        1 1  |   .5186052     .019253    26.94   0.000     .4808699    .5563404
        1 2  |   .4086182    .0192814    21.19   0.000     .3708274    .4464089
        1 3  |   .3080282    .0351181     8.77   0.000      .239198    .3768584
        2 1  |   .3034699    .0166733    18.20   0.000     .2707909    .3361489
        2 2  |   .4118523    .0182623    22.55   0.000     .3760588    .4476458
        2 3  |   .5244924    .0415791    12.61   0.000     .4429989    .6059858
        3 1  |   .1779249    .0146835    12.12   0.000     .1491458     .206704
        3 2  |   .1795295    .0177224    10.13   0.000     .1447942    .2142649
        3 3  |   .1674794    .0345493     4.85   0.000     .0997641    .2351948
------------------------------------------------------------------------------

 75 . margins, at(budget=(0 (1) 3))

Predictive margins                              Number of obs     =      1,144
Model VCE    : Robust

1._predict   : Pr(ONTvote==1), predict(pr outcome(1))
2._predict   : Pr(ONTvote==2), predict(pr outcome(2))
```

```
3._predict   : Pr(ONTvote==3), predict(pr outcome(3))

1._at        : budget          =           0

2._at        : budget          =           1

3._at        : budget          =           2

4._at        : budget          =           3
```

	Margin	Delta-method Std. Err.	z	P>|z|	[95% Conf.	Interval]
_predict#_at						
1 1	.6095718	.0399765	15.25	0.000	.5312193	.6879244
1 2	.5462724	.0256357	21.31	0.000	.4960273	.5965174
1 3	.4797621	.0143884	33.34	0.000	.4515613	.5079628
1 4	.4128725	.0195803	21.09	0.000	.3744959	.451249
2 1	.2358767	.0339353	6.95	0.000	.1693647	.3023886
2 2	.2854062	.0245081	11.65	0.000	.2373712	.3334411
2 3	.3420153	.0134629	25.40	0.000	.3156285	.3684021
2 4	.4040732	.0176042	22.95	0.000	.3695696	.4385768
3 1	.1545515	.0284884	5.43	0.000	.0987152	.2103877
3 2	.1683215	.0185755	9.06	0.000	.1319141	.2047288
3 3	.1782226	.0117491	15.17	0.000	.1551949	.2012504
3 4	.1830544	.0159849	11.45	0.000	.1517245	.2143842

```
76 . margins, at(rehabilitate=(0 (1) 10))

Predictive margins                              Number of obs     =      1,144
Model VCE    : Robust

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

1._at        : rehabilitate    =           0

2._at        : rehabilitate    =           1

3._at        : rehabilitate    =           2

4._at        : rehabilitate    =           3

5._at        : rehabilitate    =           4

6._at        : rehabilitate    =           5
```

```
7._at        : rehabilitate    =           6

8._at        : rehabilitate    =           7

9._at        : rehabilitate    =           8

10._at       : rehabilitate    =           9

11._at       : rehabilitate    =          10
```

	Delta-method Margin	Std. Err.	z	P>|z|	[95% Conf.	Interval]
_predict#_at						
1 1	.4258467	.0233806	18.21	0.000	.3800216	.4716719
1 2	.4377419	.0199029	21.99	0.000	.3987329	.4767508
1 3	.4491354	.0168661	26.63	0.000	.4160785	.4821923
1 4	.4599804	.0145942	31.52	0.000	.4313762	.4885845
1 5	.4702388	.013522	34.78	0.000	.4437362	.4967413
1 6	.4798813	.0139747	34.34	0.000	.4524914	.5072713
1 7	.4888876	.0158751	30.80	0.000	.4577729	.5200023
1 8	.4972454	.0188495	26.38	0.000	.4603011	.5341897
1 9	.5049505	.0225418	22.40	0.000	.4607693	.5491317
1 10	.5120058	.0267255	19.16	0.000	.4596248	.5643867
1 11	.5184206	.0312745	16.58	0.000	.4571238	.5797174
2 1	.4327333	.0211868	20.42	0.000	.391208	.4742587
2 2	.4128039	.0171474	24.07	0.000	.3791956	.4464121
2 3	.3932316	.0138781	28.33	0.000	.366031	.4204321
2 4	.3740921	.0118563	31.55	0.000	.3508541	.3973301
2 5	.3554511	.0114901	30.94	0.000	.3329308	.3779714
2 6	.3373634	.0126411	26.69	0.000	.3125874	.3621394
2 7	.3198731	.0147027	21.76	0.000	.2910564	.3486899
2 8	.3030135	.0171304	17.69	0.000	.2694386	.3365884
2 9	.2868074	.0196077	14.63	0.000	.248377	.3252378
2 10	.271268	.0219751	12.34	0.000	.2281976	.3143384
2 11	.2563992	.0241577	10.61	0.000	.2090509	.3037474
3 1	.14142	.0176274	8.02	0.000	.1068709	.1759691
3 2	.1494542	.015689	9.53	0.000	.1187044	.1802041
3 3	.1576331	.0138292	11.40	0.000	.1305284	.1847378
3 4	.1659275	.0123219	13.47	0.000	.141777	.190078
3 5	.1743101	.011583	15.05	0.000	.1516079	.1970124
3 6	.1827552	.012038	15.18	0.000	.1591613	.2063492
3 7	.1912393	.0138206	13.84	0.000	.1641513	.2183273
3 8	.1997411	.016721	11.95	0.000	.1669686	.2325137
3 9	.2082421	.0204423	10.19	0.000	.1681759	.2483083
3 10	.2167262	.0247618	8.75	0.000	.1681939	.2652585
3 11	.2251803	.0295393	7.62	0.000	.1672843	.2830762

```
77 . margins, at(fewerimmigrants=(0 (1) 10))

Predictive margins                              Number of obs     =      1,144
Model VCE    : Robust

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

1._at        : fewerimmig~s    =           0

2._at        : fewerimmig~s    =           1

3._at        : fewerimmig~s    =           2

4._at        : fewerimmig~s    =           3

5._at        : fewerimmig~s    =           4

6._at        : fewerimmig~s    =           5

7._at        : fewerimmig~s    =           6

8._at        : fewerimmig~s    =           7

9._at        : fewerimmig~s    =           8

10._at       : fewerimmig~s    =           9

11._at       : fewerimmig~s    =          10
```

_predict#_at	Margin	Delta-method Std. Err.	z	P>|z|	[95% Conf.	Interval]
1 1	.5293299	.0374616	14.13	0.000	.4559065	.6027533
1 2	.5201361	.0322523	16.13	0.000	.4569227	.5833496
1 3	.510805	.0272311	18.76	0.000	.457433	.5641771
1 4	.5013419	.0225155	22.27	0.000	.4572122	.5454715
1 5	.4917532	.0183247	26.84	0.000	.4558375	.527669
1 6	.482047	.0150696	31.99	0.000	.4525111	.5115828
1 7	.4722323	.0133984	35.25	0.000	.445972	.4984927
1 8	.4623198	.0138328	33.42	0.000	.435208	.4894316
1 9	.4523213	.0161378	28.03	0.000	.4206917	.4839508
1 10	.4422497	.0195997	22.56	0.000	.403835	.4806643
1 11	.4321192	.0236514	18.27	0.000	.3857632	.4784751

2 1	**.2868284**	**.026978**	**10.63**	**0.000**	**.2339525**	**.3397043**
2 2	**.2967026**	**.024039**	**12.34**	**0.000**	**.2495871**	**.3438181**
2 3	**.3068478**	**.021**	**14.61**	**0.000**	**.2656886**	**.348007**
2 4	**.3172609**	**.017944**	**17.68**	**0.000**	**.2820914**	**.3524304**
2 5	**.3279368**	**.0150345**	**21.81**	**0.000**	**.2984697**	**.3574039**
2 6	**.3388686**	**.0125954**	**26.90**	**0.000**	**.3141821**	**.363555**
2 7	**.3500471**	**.0112**	**31.25**	**0.000**	**.3280955**	**.3719986**
2 8	**.3614611**	**.0114904**	**31.46**	**0.000**	**.3389403**	**.3839819**
2 9	**.3730975**	**.0135566**	**27.52**	**0.000**	**.3465271**	**.399668**
2 10	**.384941**	**.0169002**	**22.78**	**0.000**	**.3518171**	**.4180648**
2 11	**.3969742**	**.0210188**	**18.89**	**0.000**	**.3557782**	**.4381703**
3 1	**.1838417**	**.0328389**	**5.60**	**0.000**	**.1194787**	**.2482047**
3 2	**.1831613**	**.0280716**	**6.52**	**0.000**	**.128142**	**.2381805**
3 3	**.1823472**	**.0235067**	**7.76**	**0.000**	**.1362749**	**.2284195**
3 4	**.1813972**	**.0192515**	**9.42**	**0.000**	**.1436649**	**.2191296**
3 5	**.18031**	**.0155075**	**11.63**	**0.000**	**.1499158**	**.2107041**
3 6	**.1790845**	**.0126563**	**14.15**	**0.000**	**.1542785**	**.2038904**
3 7	**.1777206**	**.0112914**	**15.74**	**0.000**	**.1555899**	**.1998513**
3 8	**.1762191**	**.0118299**	**14.90**	**0.000**	**.1530328**	**.1994053**
3 9	**.1745812**	**.0139581**	**12.51**	**0.000**	**.1472238**	**.2019386**
3 10	**.1728094**	**.0170062**	**10.16**	**0.000**	**.1394779**	**.2061409**
3 11	**.1709066**	**.0204928**	**8.34**	**0.000**	**.1307415**	**.2110717**

```
78 . margins, dydx(antiniqab)

Average marginal effects                        Number of obs     =      1,144
Model VCE    : Robust

dy/dx w.r.t. : 1.antiniqab
1._predict   : Pr(ONTvote==1), predict(pr outcome(1))
2._predict   : Pr(ONTvote==2), predict(pr outcome(2))
3._predict   : Pr(ONTvote==3), predict(pr outcome(3))
```

	Delta-method					
	dy/dx	Std. Err.	z	P>|z|	[95% Conf.	Interval]
1.antiniqab						
_predict						
1	**-.0346606**	**.0321962**	**-1.08**	**0.282**	**-.0977641**	**.0284428**
2	**.0542802**	**.0281235**	**1.93**	**0.054**	**-.0008407**	**.1094012**
3	**-.0196196**	**.0285757**	**-0.69**	**0.492**	**-.0756269**	**.0363877**

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

79 . margins, at(corruption=(0 1 2))

Predictive margins                              Number of obs     =      1,144
```

```
Model VCE    : Robust

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

1._at        : corruption      =          0

2._at        : corruption      =          1

3._at        : corruption      =          2
```

	Margin	Delta-method Std. Err.	z	P>|z|	[95% Conf.	Interval]
_predict#_at						
1 1	.4238383	.0242824	17.45	0.000	.3762457	.4714309
1 2	.4706284	.0139415	33.76	0.000	.4433035	.4979532
1 3	.5104245	.0207014	24.66	0.000	.4698506	.5509985
2 1	.4297579	.0204777	20.99	0.000	.3896224	.4698934
2 2	.3551667	.0118768	29.90	0.000	.3318885	.3784449
2 3	.2879543	.0186009	15.48	0.000	.2514973	.3244113
3 1	.1464038	.0190612	7.68	0.000	.1090445	.1837631
3 2	.174205	.0119466	14.58	0.000	.1507901	.1976199
3 3	.2016212	.0189216	10.66	0.000	.1645356	.2387068

```
80 .
81 . *** Leadership
82 .
83 . mlogit ONTvote i.female i.older i.lowinc i.missingincome i.HSorless i.university
   >  i.French i.visible i.catholic i.noreligion i.working i.union i.bigcity antiredi
   > stribute IDliberal IDconservative IDndp sociotropic budget i.antiniqab rehabilit
   > ate fewerimmigrants corruption Trudeau Harper mulcair if Province==35  [iweight=
   > regionWT], robust

Iteration 0:   log pseudolikelihood =  -1145.875
Iteration 1:   log pseudolikelihood = -530.56026
Iteration 2:   log pseudolikelihood = -484.76049
Iteration 3:   log pseudolikelihood = -445.25727
Iteration 4:   log pseudolikelihood = -442.10662
Iteration 5:   log pseudolikelihood = -442.09093
Iteration 6:   log pseudolikelihood = -442.08917
Iteration 7:   log pseudolikelihood = -442.08883
Iteration 8:   log pseudolikelihood = -442.08876
Iteration 9:   log pseudolikelihood = -442.08874

Multinomial logistic regression                 Number of obs     =      1,144
```

	Wald chi2(**52**)	=	**857.19**
	Prob > chi2	=	**0.0000**
Log pseudolikelihood = **-442.08874**	Pseudo R2	=	**0.6142**

ONTvote	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
1	(base outcome)					
2						
1.female	**.1487054**	**.3217173**	**0.46**	**0.644**	**-.481849**	**.7792598**
1.older	**-.4545732**	**.3541943**	**-1.28**	**0.199**	**-1.148781**	**.2396348**
1.lowinc	**.0861325**	**.3903588**	**0.22**	**0.825**	**-.6789567**	**.8512217**
1.missingincome	**.5333114**	**.5345561**	**1.00**	**0.318**	**-.5143994**	**1.581022**
1.HSorless	**.0554561**	**.393159**	**0.14**	**0.888**	**-.7151213**	**.8260335**
1.university	**-.3226734**	**.360099**	**-0.90**	**0.370**	**-1.028454**	**.3831078**
1.French	**-.2819769**	**.9980193**	**-0.28**	**0.778**	**-2.238059**	**1.674105**
1.visible	**-.6992403**	**.3756502**	**-1.86**	**0.063**	**-1.435501**	**.0370205**
1.catholic	**-1.12567**	**.3608106**	**-3.12**	**0.002**	**-1.832846**	**-.4184942**
1.noreligion	**-.466964**	**.3687221**	**-1.27**	**0.205**	**-1.189646**	**.2557181**
1.working	**-.0101267**	**.3386113**	**-0.03**	**0.976**	**-.6737927**	**.6535393**
1.union	**-.4537475**	**.3578194**	**-1.27**	**0.205**	**-1.155061**	**.2475656**
1.bigcity	**-.3257705**	**.3353321**	**-0.97**	**0.331**	**-.9830094**	**.3314685**
antiredistribute	**.0670154**	**.0637953**	**1.05**	**0.293**	**-.058021**	**.1920518**
IDliberal	**-1.485862**	**.7773445**	**-1.91**	**0.056**	**-3.009429**	**.0377053**
IDconservative	**1.255879**	**.4975712**	**2.52**	**0.012**	**.2806573**	**2.231101**
IDndp	**-13.59873**	**.8332242**	**-16.32**	**0.000**	**-15.23182**	**-11.96564**
sociotropic	**.6323373**	**.2912204**	**2.17**	**0.030**	**.0615558**	**1.203119**
budget	**.4331763**	**.202661**	**2.14**	**0.033**	**.0359681**	**.8303846**
1.antiniqab	**.4209579**	**.3404774**	**1.24**	**0.216**	**-.2463655**	**1.088281**
rehabilitate	**-.0988104**	**.0621959**	**-1.59**	**0.112**	**-.2207122**	**.0230913**
fewerimmigrants	**.0168415**	**.0725926**	**0.23**	**0.817**	**-.1254375**	**.1591204**
corruption	**.0036622**	**.2253555**	**0.02**	**0.987**	**-.4380265**	**.4453509**
Trudeau	**-.669492**	**.0885638**	**-7.56**	**0.000**	**-.8430739**	**-.4959101**
Harper	**.5610513**	**.0835307**	**6.72**	**0.000**	**.3973342**	**.7247685**
mulcair	**-.0131011**	**.0821827**	**-0.16**	**0.873**	**-.1741762**	**.1479739**
_cons	**.5472955**	**1.15417**	**0.47**	**0.635**	**-1.714835**	**2.809426**
3						
1.female	**.4195831**	**.2485444**	**1.69**	**0.091**	**-.067555**	**.9067213**
1.older	**-.8191531**	**.334545**	**-2.45**	**0.014**	**-1.474849**	**-.1634569**
1.lowinc	**.4363398**	**.2876795**	**1.52**	**0.129**	**-.1275017**	**1.000181**
1.missingincome	**.5616421**	**.5055234**	**1.11**	**0.267**	**-.4291654**	**1.55245**
1.HSorless	**.690511**	**.3231794**	**2.14**	**0.033**	**.0570911**	**1.323931**
1.university	**-.2600872**	**.2741754**	**-0.95**	**0.343**	**-.7974611**	**.2772867**
1.French	**1.036084**	**.7249939**	**1.43**	**0.153**	**-.3848784**	**2.457045**
1.visible	**-.9259455**	**.3750975**	**-2.47**	**0.014**	**-1.661123**	**-.1907679**
1.catholic	**-.0648492**	**.3179419**	**-0.20**	**0.838**	**-.6880038**	**.5583054**

1.noreligion	-.1497671	.2988777	-0.50	0.616	-.7355566	.4360224
1.working	-.7012792	.2886305	-2.43	0.015	-1.266985	-.1355739
1.union	.3371146	.296508	1.14	0.256	-.2440304	.9182595
1.bigcity	.2186159	.2669393	0.82	0.413	-.3045755	.7418073
antiredistribute	.0195528	.0539031	0.36	0.717	-.0860953	.125201
IDliberal	-2.0403	.6337087	-3.22	0.001	-3.282347	-.7982542
IDconservative	.1703476	.7852519	0.22	0.828	-1.368718	1.709413
IDndp	.8923442	.4215811	2.12	0.034	.0660606	1.718628
sociotropic	.5648681	.2640297	2.14	0.032	.0473793	1.082357
budget	.1689773	.1410507	1.20	0.231	-.1074769	.4454315
1.antiniqab	.2276005	.2965771	0.77	0.443	-.35368	.808881
rehabilitate	-.0071428	.0460574	-0.16	0.877	-.0974137	.0831281
fewerimmigrants	-.0100501	.0598623	-0.17	0.867	-.127378	.1072778
corruption	.0912393	.1850354	0.49	0.622	-.2714233	.453902
Trudeau	-.669143	.079763	-8.39	0.000	-.8254757	-.5128103
Harper	-.1020081	.0630489	-1.62	0.106	-.2255816	.0215654
mulcair	.721544	.081347	8.87	0.000	.5621068	.8809812
_cons	-1.132172	.9253104	-1.22	0.221	-2.945747	.6814034

```
84 . mlogit ONTvote i.female i.older i.lowinc i.missingincome i.HSorless i.university
   >  i.French i.visible i.catholic i.noreligion i.working i.union i.bigcity antiredi
   > stribute IDliberal IDconservative IDndp sociotropic budget i.antiniqab rehabilit
   > ate fewerimmigrants corruption Trudeau Harper mulcair if Province==35  [iweight=
   > regionWT], baseoutcome(2) robust

Iteration 0:   log pseudolikelihood =  -1145.875
Iteration 1:   log pseudolikelihood = -530.56026
Iteration 2:   log pseudolikelihood = -484.76049
Iteration 3:   log pseudolikelihood = -445.25727
Iteration 4:   log pseudolikelihood = -442.10662
Iteration 5:   log pseudolikelihood = -442.09093
Iteration 6:   log pseudolikelihood = -442.08917
Iteration 7:   log pseudolikelihood = -442.08883
Iteration 8:   log pseudolikelihood = -442.08876
Iteration 9:   log pseudolikelihood = -442.08874

Multinomial logistic regression                 Number of obs     =      1,144
                                                Wald chi2(52)     =     856.49
                                                Prob > chi2       =     0.0000
Log pseudolikelihood = -442.08874               Pseudo R2         =     0.6142
```

ONTvote	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
1						
1.female	-.1487054	.3217173	-0.46	0.644	-.7792598	.481849
1.older	.4545732	.3541943	1.28	0.199	-.2396348	1.148781

1.lowinc	-.0861325	.3903588	-0.22	0.825	-.8512217	.6789567
1.missingincome	-.5333114	.5345561	-1.00	0.318	-1.581022	.5143994
1.HSorless	-.0554561	.393159	-0.14	0.888	-.8260335	.7151213
1.university	.3226734	.360099	0.90	0.370	-.3831078	1.028454
1.French	.2819769	.9980193	0.28	0.778	-1.674105	2.238059
1.visible	.6992403	.3756502	1.86	0.063	-.0370205	1.435501
1.catholic	1.12567	.3608106	3.12	0.002	.4184942	1.832846
1.noreligion	.466964	.3687221	1.27	0.205	-.2557181	1.189646
1.working	.0101267	.3386113	0.03	0.976	-.6535393	.6737927
1.union	.4537475	.3578194	1.27	0.205	-.2475656	1.155061
1.bigcity	.3257705	.3353321	0.97	0.331	-.3314685	.9830094
antiredistribute	-.0670154	.0637953	-1.05	0.293	-.1920518	.058021
IDliberal	1.485862	.7773445	1.91	0.056	-.0377053	3.009429
IDconservative	-1.255879	.4975712	-2.52	0.012	-2.231101	-.2806573
IDndp	13.59873	.8335951	16.31	0.000	11.96492	15.23255
sociotropic	-.6323373	.2912204	-2.17	0.030	-1.203119	-.0615558
budget	-.4331763	.202661	-2.14	0.033	-.8303846	-.0359681
1.antiniqab	-.4209579	.3404774	-1.24	0.216	-1.088281	.2463655
rehabilitate	.0988104	.0621959	1.59	0.112	-.0230913	.2207122
fewerimmigrants	-.0168415	.0725926	-0.23	0.817	-.1591204	.1254375
corruption	-.0036622	.2253555	-0.02	0.987	-.4453509	.4380265
Trudeau	.669492	.0885638	7.56	0.000	.4959101	.8430739
Harper	-.5610513	.0835307	-6.72	0.000	-.7247685	-.3973342
mulcair	.0131011	.0821827	0.16	0.873	-.1479739	.1741762
_cons	-.5472955	1.15417	-0.47	0.635	-2.809426	1.714835
2	(base outcome)					
3						
1.female	.2708777	.3557836	0.76	0.446	-.4264453	.9682008
1.older	-.3645799	.4031047	-0.90	0.366	-1.154651	.4254909
1.lowinc	.3502073	.4333046	0.81	0.419	-.4990541	1.199469
1.missingincome	.0283307	.5505143	0.05	0.959	-1.050657	1.107319
1.HSorless	.6350549	.3867147	1.64	0.101	-.122892	1.393002
1.university	.0625862	.3764049	0.17	0.868	-.6751538	.8003261
1.French	1.31806	.9883464	1.33	0.182	-.6190628	3.255184
1.visible	-.2267051	.440262	-0.51	0.607	-1.089603	.6361926
1.catholic	1.060821	.3803685	2.79	0.005	.3153121	1.806329
1.noreligion	.3171969	.390817	0.81	0.417	-.4487904	1.083184
1.working	-.6911525	.3764941	-1.84	0.066	-1.429067	.0467624
1.union	.790862	.3570608	2.21	0.027	.0910357	1.490688
1.bigcity	.5443864	.3736901	1.46	0.145	-.1880327	1.276805
antiredistribute	-.0474625	.0718378	-0.66	0.509	-.188262	.0933369
IDliberal	-.5544384	.9794578	-0.57	0.571	-2.47414	1.365264
IDconservative	-1.085531	.7256207	-1.50	0.135	-2.507722	.3366591
IDndp	14.49108	.9190547	15.77	0.000	12.68976	16.29239
sociotropic	-.0674692	.2973214	-0.23	0.820	-.6502084	.51527
budget	-.264199	.1926186	-1.37	0.170	-.6417245	.1133265
1.antiniqab	-.1933574	.3662935	-0.53	0.598	-.9112795	.5245647

rehabilitate	.0916676	.0680154	1.35	0.178	-.0416401	.2249753
fewerimmigrants	-.0268915	.0767385	-0.35	0.726	-.1772962	.1235131
corruption	.0875771	.2329335	0.38	0.707	-.3689641	.5441183
Trudeau	.000349	.0648471	0.01	0.996	-.1267491	.127447
Harper	-.6630594	.0829625	-7.99	0.000	-.825663	-.5004558
mulcair	.7346451	.0869078	8.45	0.000	.564309	.9049813
_cons	-1.679467	1.239421	-1.36	0.175	-4.108688	.7497533

```
85 .
86 . margins, at(Trudeau=(0 (1) 10))

Predictive margins                              Number of obs     =      1,144
Model VCE    : Robust

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

1._at        : Trudeau         =           0

2._at        : Trudeau         =           1

3._at        : Trudeau         =           2

4._at        : Trudeau         =           3

5._at        : Trudeau         =           4

6._at        : Trudeau         =           5

7._at        : Trudeau         =           6

8._at        : Trudeau         =           7

9._at        : Trudeau         =           8

10._at       : Trudeau         =           9

11._at       : Trudeau         =          10
```

	Margin	Delta-method Std. Err.	z	P>|z|	[95% Conf.	Interval]
_predict#_at						
1 1	.0725305	.0223971	3.24	0.001	.028633	.1164281
1 2	.1053804	.0252667	4.17	0.000	.0558586	.1549022
1 3	.1480007	.0267862	5.53	0.000	.0955006	.2005007

1 4	.2015987	.0264225	7.63	0.000	.1498115	.2533859
1 5	.2665847	.0239244	11.14	0.000	.2196937	.3134758
1 6	.3420201	.0197647	17.30	0.000	.3032821	.3807582
1 7	.4254307	.0157886	26.95	0.000	.3944855	.4563758
1 8	.5129485	.0154042	33.30	0.000	.4827568	.5431402
1 9	.5997973	.0194485	30.84	0.000	.5616791	.6379156
1 10	.6813668	.0248747	27.39	0.000	.6326134	.7301203
1 11	.7543639	.0295714	25.51	0.000	.696405	.8123228
2 1	.4810719	.0265539	18.12	0.000	.4290271	.5331166
2 2	.4689297	.022102	21.22	0.000	.4256106	.5122489
2 3	.4534083	.0181833	24.94	0.000	.4177695	.489047
2 4	.4337586	.0149516	29.01	0.000	.4044539	.4630633
2 5	.4092538	.0125113	32.71	0.000	.3847321	.4337755
2 6	.3794469	.0110483	34.34	0.000	.3577926	.4011011
2 7	.3444253	.0110704	31.11	0.000	.3227278	.3661228
2 8	.3050619	.0130302	23.41	0.000	.2795232	.3306005
2 9	.2630253	.0165251	15.92	0.000	.2306366	.2954139
2 10	.2203009	.0206715	10.66	0.000	.1797854	.2608163
2 11	.1786368	.0247179	7.23	0.000	.1301905	.227083
3 1	.4463976	.0308862	14.45	0.000	.3858617	.5069335
3 2	.4256898	.0286288	14.87	0.000	.3695785	.4818012
3 3	.3985911	.0264382	15.08	0.000	.3467731	.4504091
3 4	.3646427	.0237314	15.37	0.000	.3181301	.4111554
3 5	.3241614	.0201885	16.06	0.000	.2845926	.3637303
3 6	.278533	.0161025	17.30	0.000	.2469728	.3100933
3 7	.230144	.0124992	18.41	0.000	.205646	.254642
3 8	.1819896	.0107102	16.99	0.000	.160998	.2029813
3 9	.1371774	.0108197	12.68	0.000	.1159712	.1583836
3 10	.0983323	.0113206	8.69	0.000	.0761442	.1205203
3 11	.0669993	.0110812	6.05	0.000	.0452806	.0887181

```
87 . marginsplot, recast(line) recastci(rarea)

  Variables that uniquely identify margins: Trudeau _outcome

88 . margins, at(Harper=(0 (1) 10))

Predictive margins                              Number of obs     =      1,144
Model VCE    : Robust

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

1._at        : Harper          =           0

2._at        : Harper          =           1
```

```
3._at        : Harper        =        2

4._at        : Harper        =        3

5._at        : Harper        =        4

6._at        : Harper        =        5

7._at        : Harper        =        6

8._at        : Harper        =        7

9._at        : Harper        =        8

10._at       : Harper        =        9

11._at       : Harper        =       10
```

	Margin	Delta-method Std. Err.	z	P>|z|	[95% Conf.	Interval]
_predict#_at						
1 1	.5588581	.0285493	19.58	0.000	.5029026	.6148137
1 2	.5547863	.0229621	24.16	0.000	.5097814	.5997913
1 3	.5466418	.0186532	29.31	0.000	.5100823	.5832014
1 4	.5336737	.0159714	33.41	0.000	.5023704	.5649771
1 5	.515234	.0150785	34.17	0.000	.4856807	.5447873
1 6	.4909845	.0159687	30.75	0.000	.4596864	.5222826
1 7	.4610343	.018655	24.71	0.000	.4244712	.4975974
1 8	.4259449	.0230349	18.49	0.000	.3807973	.4710925
1 9	.3866955	.0286859	13.48	0.000	.3304723	.4429188
1 10	.3446446	.0349637	9.86	0.000	.2761169	.4131723
1 11	.3013953	.0411918	7.32	0.000	.2206608	.3821297
2 1	.111652	.0261898	4.26	0.000	.0603209	.1629832
2 2	.1436162	.0262302	5.48	0.000	.0922059	.1950264
2 3	.1815402	.0250533	7.25	0.000	.1324366	.2306438
2 4	.2256581	.0225438	10.01	0.000	.1814731	.269843
2 5	.2756506	.0188864	14.60	0.000	.2386339	.3126672
2 6	.3305688	.0152918	21.62	0.000	.3005973	.3605403
2 7	.3891071	.0147086	26.45	0.000	.3602789	.4179354
2 8	.449934	.0189875	23.70	0.000	.4127192	.4871489
2 9	.5117069	.026067	19.63	0.000	.4606166	.5627972
2 10	.5729099	.0337482	16.98	0.000	.5067646	.6390553
2 11	.6318667	.0408157	15.48	0.000	.5518693	.711864
3 1	.3294898	.033838	9.74	0.000	.2631685	.3958111
3 2	.3015975	.0284136	10.61	0.000	.2459079	.3572871
3 3	.271818	.0236403	11.50	0.000	.2254839	.3181521
3 4	.2406682	.0196845	12.23	0.000	.2020874	.279249

	Margin	Std. Err.	z	P>|z|	[95% Conf.	Interval]
3 5	.2091154	.0168599	12.40	0.000	.1760706	.2421603
3 6	.1784467	.0155179	11.50	0.000	.1480322	.2088613
3 7	.1498586	.0154843	9.68	0.000	.11951	.1802072
3 8	.1241211	.0159561	7.78	0.000	.0928477	.1553945
3 9	.1015976	.0161841	6.28	0.000	.0698774	.1333178
3 10	.0824454	.0158226	5.21	0.000	.0514336	.1134572
3 11	.0667381	.0148472	4.49	0.000	.0376381	.0958381

```
89 . marginsplot, recast(line) recastci(rarea)

  Variables that uniquely identify margins: Harper _outcome

90 . margins, at(mulcair=(0 (1) 10))

Predictive margins                              Number of obs     =      1,144
Model VCE    : Robust

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

1._at        : mulcair         =           0

2._at        : mulcair         =           1

3._at        : mulcair         =           2

4._at        : mulcair         =           3

5._at        : mulcair         =           4

6._at        : mulcair         =           5

7._at        : mulcair         =           6

8._at        : mulcair         =           7

9._at        : mulcair         =           8

10._at       : mulcair         =           9

11._at       : mulcair         =          10
```

	Delta-method					
	Margin	Std. Err.	z	P>|z|	[95% Conf.	Interval]
_predict#_at						

1 1	.5905217	.0239875	24.62	0.000	.5435071	.6375364
1 2	.5870268	.020054	29.27	0.000	.5477218	.6263319
1 3	.5809172	.0165648	35.07	0.000	.5484508	.6133835
1 4	.570826	.0137916	41.39	0.000	.543795	.597857
1 5	.5548974	.0119659	46.37	0.000	.5314447	.5783501
1 6	.531016	.0110657	47.99	0.000	.5093276	.5527045
1 7	.4973037	.0109631	45.36	0.000	.4758163	.518791
1 8	.4528554	.0120003	37.74	0.000	.4293352	.4763756
1 9	.3986368	.0148132	26.91	0.000	.3696035	.4276702
1 10	.3378498	.0190714	17.72	0.000	.3004706	.375229
1 11	.2751133	.0235262	11.69	0.000	.2290029	.3212238
2 1	.4014563	.0236583	16.97	0.000	.355087	.4478257
2 2	.398663	.0195248	20.42	0.000	.360395	.4369309
2 3	.3945361	.0156712	25.18	0.000	.3638211	.4252511
2 4	.3884332	.0122818	31.63	0.000	.3643613	.4125051
2 5	.3795053	.0096965	39.14	0.000	.3605006	.39851
2 6	.3667229	.0084602	43.35	0.000	.3501412	.3833045
2 7	.3489665	.0090311	38.64	0.000	.3312659	.3666671
2 8	.3252932	.0113902	28.56	0.000	.3029688	.3476176
2 9	.2953471	.0153714	19.21	0.000	.2652198	.3254744
2 10	.2596374	.0207488	12.51	0.000	.2189705	.3003044
2 11	.2196108	.0268686	8.17	0.000	.1669493	.2722724
3 1	.0080219	.0032144	2.50	0.013	.0017218	.0143221
3 2	.0143102	.004568	3.13	0.002	.005357	.0232633
3 3	.0245467	.0061655	3.98	0.000	.0124625	.036631
3 4	.0407408	.0079141	5.15	0.000	.0252294	.0562521
3 5	.0655973	.0094971	6.91	0.000	.0469833	.0842114
3 6	.1022611	.010477	9.76	0.000	.0817266	.1227956
3 7	.1537298	.0109699	14.01	0.000	.1322293	.1752303
3 8	.2218513	.0128022	17.33	0.000	.1967596	.2469431
3 9	.3060161	.0185097	16.53	0.000	.2697378	.3422943
3 10	.4025128	.0276413	14.56	0.000	.3483369	.4566887
3 11	.5052758	.0378292	13.36	0.000	.4311319	.5794198

```
91 . marginsplot, recast(line) recastci(rarea)

  Variables that uniquely identify margins: mulcair _outcome

92 .
end of do-file

93 . log close
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       log:  /Users/elisabethgidengil/Documents/Blais MCRI/Region/Ontario MNL.smcl
  log type:  smcl
 closed on:   1 Sep 2016, 17:31:28
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