# What is Multinomial Logistic Regression and how can it be applied in Stata for data analysis?

Authored by
**stats writer**

June 29, 2024

Multinomial Logistic Regression is a statistical technique used to analyze the relationship between multiple independent variables and a categorical dependent variable with more than two categories. It is an extension of the binary logistic regression, which is used for binary outcomes. In Multinomial Logistic Regression, the dependent variable can have three or more possible outcomes, making it suitable for analyzing complex relationships in data.

In Stata, Multinomial Logistic Regression can be applied for data analysis through the "mlogit" command. This command allows users to specify the categorical dependent variable and the independent variables to be included in the model. Stata also provides options for assessing the model fit, such as the likelihood ratio test and the McFadden's pseudo R-squared. Additionally, the "margins" command can be used to estimate predicted probabilities for each category of the dependent variable, providing insights into the relationship between the independent variables and the different outcomes.

Multinomial Logistic Regression in Stata can be applied in various fields, such as social sciences, business, and healthcare, to understand and predict the likelihood of different outcomes based on a set of variables. It is a powerful tool for analyzing complex data and can provide valuable insights for decision making and policy planning.

## Multinomial Logistic Regression | Stata Data Analysis Examples

## Version info: Code for this page was tested in Stata 12.

## Multinomial logistic regression is used to model nominal
## outcome variables, in which the log odds of the outcomes are modeled as a linear
## combination of the predictor variables.

## Please note: The purpose of this page is to show how to use various data analysis commands.

**It does not cover all aspects of the research process which researchers are expected to do. In particular, it does not cover data cleaning and checking, verification of assumptions, model diagnostics and potential follow-up analyses.**

### Examples of multinomial logistic regression

**Example 1. People's occupational choices might be influenced by their parents' occupations and their own education level. We can study the relationship of one's occupation choice with education level and father's occupation. The occupational choices will be the outcome variable which consists of categories of occupations.**

**Example 2. A biologist may be interested in food choices that alligators make. Adult alligators might have different preferences from young ones. The outcome variable here will be the types of food, and the predictor variables might be size of the alligators**

and other environmental variables.

Example 3. Entering high school students make program choices among general program,
vocational program and academic program. Their choice might be modeled using
their writing score and their social economic status.

Description of the data

For our data analysis example, we will expand the third example using the
hsbdemo data set. Let's first read in the data.

use https://stats.idre.ucla.edu/stat/data/hsbdemo, clear

The data set contains variables on 200 students. The outcome variable is prog, program type. The predictor variables
are social economic status, ses, a three-level categorical variable
and writing score, write, a continuous variable. Let's start with
getting some descriptive statistics of the
variables of interest.

```
tab prog ses, chi2

type of | ses
program | low middle high | Total
-----------+--------------------------------+----------
general | 16 20 9 | 45
academic | 19 44 42 | 105
vocation | 12 31 7 | 50
-----------+--------------------------------+----------
Total | 47 95 58 | 200

Pearson chi2(4) = 16.6044 Pr = 0.002


table prog, con(mean write sd write)


----------------------------------
type of |
program | mean(write) sd(write)
----------+-----------------------
general | 51.33333 9.397776
academic | 56.25714 7.943343
vocation | 46.76 9.318754
----------------------------------
```

## Analysis methods you might consider

## Multinomial logistic regression

**Below we use the mlogit command to estimate a multinomial logistic regression model. The i. before ses indicates that ses is a indicator variable (i.e., categorical variable), and that it should be included in the model. We have also used the option "base" to indicate the category we would want to use for the baseline comparison group. In the model below, we have chosen to use the academic program type as the baseline category.**

**mlogit prog i.ses write, base(2)**

**Iteration 0: log likelihood = -204.09667**
**Iteration 1: log likelihood = -180.80105**
**Iteration 2: log likelihood = -179.98724**
**Iteration 3: log likelihood = -179.98173**
**Iteration 4: log likelihood = -179.98173**

**Multinomial logistic regression Number of obs = 200**

LR chi2(6) = 48.23

Prob > chi2 = 0.0000

Log likelihood = -179.98173 Pseudo R2 = 0.1182

------------------------------------------------------------------------------

prog | Coef. Std. Err. z P>|z|

-------------+----------------------------------------------------------------

general |

ses |

2 | -.533291 .4437321 -1.20 0.229 -1.40299 .336408

3 | -1.162832 .5142195 -2.26 0.024 -2.170684 -.1549804

|

write | -.0579284 .0214109 -2.71 0.007 -.0998931 -.0159637

_cons | 2.852186 1.166439 2.45 0.014 .5660075 5.138365

-------------+----------------------------------------------------------------

academic | (base outcome)

-------------+----------------------------------------------------------------

vocation |

ses |

2 | .2913931 .4763737 0.61 0.541 -.6422822 1.225068

3 | -.9826703 .5955669 -1.65 0.099 -2.14996 .1846195

|

write | -.1136026 .0222199 -5.11 0.000 -.1571528 -

**.0700524**

**_cons | 5.2182 1.163549 4.48 0.000 2.937686 7.498714**

**------------------------------------------------------------------------------**

**The ratio of the probability of choosing one outcome category over the probability of choosing the baseline category is often referred to as relative risk (and it is also sometimes referred to as odds as we have just used to described the regression parameters above). Relative risk can be obtained by exponentiating the linear equations above, yielding regression coefficients that are relative risk ratios for a unit change in the predictor variable. We can use the rrr option for mlogit command to display the regression results in terms of relative risk ratios.**

**mlogit, rrr**

**Multinomial logistic regression Number of obs = 200**

**LR chi2(6) = 48.23**

Prob > chi2 = 0.0000

Log likelihood = -179.98173 Pseudo R2 = 0.1182

------------------------------------------------------------------------------

prog | RRR Std. Err. z P>|z|

-------------+----------------------------------------------------------------

general |

ses |

2 | .586671 .2603248 -1.20 0.229 .2458607 1.39991

3 | .3125996 .1607448 -2.26 0.024 .1140996 .856432

|

write | .9437175 .0202059 -2.71 0.007 .9049342 .984163

_cons | 17.32562 20.20928 2.45 0.014 1.761221 170.4369

-------------+----------------------------------------------------------------

academic | (base outcome)

-------------+----------------------------------------------------------------

vocation |

ses |

2 | 1.338291 .6375264 0.61 0.541 .5260904 3.404399

3 | .3743103 .2229268 -1.65 0.099 .1164888 1.202761

|

write | .8926126 .0198338 -5.11 0.000 .8545734 .9323449

_cons | 184.6016 214.793 4.48 0.000 18.87213 1805.719

------------------------------------------------------------------------------

**We can test for an overall effect of ses using the test command. Below we see that the overall effect of ses is statistically significant.**

**test 2.ses 3.ses**

**( 1) 2.ses = 0**
**( 2) 2.ses = 0**
**( 3) 2.ses = 0**
**( 4) 3.ses = 0**
**( 5) 3.ses = 0**
**( 6) 3.ses = 0**
**Constraint 2 dropped**
**Constraint 5 dropped**

**chi2( 4) = 10.82**
**Prob > chi2 = 0.0287**

**More specifically, we can also test if the effect of 3.ses in predicting general vs. academic equals the effect of 3.ses in predicting vocation vs. academic using the test**

**command again. The test shows that the effects are not statistically different from each other.**

**test 3.ses = 3.ses**

**( 1) 3.ses - 3.ses = 0**

**chi2( 1) = 0.08**
**Prob > chi2 = 0.7811**

**You can also use predicted probabilities to help you understand the model.**
**You can calculate predicted probabilities using the margins command. Below we use the margins command to calculate the predicted probability of choosing each program type at each level of ses, holding all other variables in the model at their means. Since there are three possible outcomes, we will need to use the margins command three times, one for each outcome value.**

**margins ses, atmeans predict(outcome(1))**

**Adjusted predictions Number of obs = 200**

**Model VCE : OIM**

**Expression : Pr(prog==general), predict(outcome(1))**

**at : 1.ses = .235 (mean)**

**2.ses = .475 (mean)**

**3.ses = .29 (mean)**

**write = 52.775 (mean)**

**------------------------------------------------------------------------------**

**| Delta-method**

**| Margin Std. Err. z P>|z|**

**-------------+----------------------------------------------------------------**

**ses |**

**1 | .3581927 .0726423 4.93 0.000 .2158163 .500569**

**2 | .2283338 .0451162 5.06 0.000 .1399075 .31676**

**3 | .1784932 .0540486 3.30 0.001 .0725598 .2844266**

**------------------------------------------------------------------------------**

**margins ses, atmeans predict(outcome(2))**

**Adjusted predictions Number of obs = 200**

**Model VCE : OIM**

**Expression : Pr(prog==academic), predict(outcome(2))**

**at : 1.ses = .235 (mean)**

**2.ses = .475 (mean)**

**3.ses = .29 (mean)**

**write = 52.775 (mean)**

**------------------------------------------------------------------------------**

**| Delta-method**

**| Margin Std. Err. z P>|z|**

**-------------+----------------------------------------------------------------**

**ses |**

**1 | .4396842 .0779925 5.64 0.000 .2868217 .5925466**

**2 | .4777488 .0552593 8.65 0.000 .3694426 .586055**

**3 | .7009021 .0663042 10.57 0.000 .5709483 .8308559**

**------------------------------------------------------------------------------**

**margins ses, atmeans predict(outcome(3))**

**Adjusted predictions Number of obs = 200**

**Model VCE : OIM**

**Expression : Pr(prog==vocation), predict(outcome(3))**

**at : 1.ses = .235 (mean)**

**2.ses = .475 (mean)**

**3.ses = .29 (mean)**

write = 52.775 (mean)

------------------------------------------------------------------------------

| Delta-method

| Margin Std. Err. z P>|z|

-------------+----------------------------------------------------------------

ses |

1 | .2021232 .0599647 3.37 0.001 .0845945 .3196519

2 | .2939174 .0503617 5.84 0.000 .1952103 .3926246

3 | .1206047 .04643 2.60 0.009 .0296037 .2116058

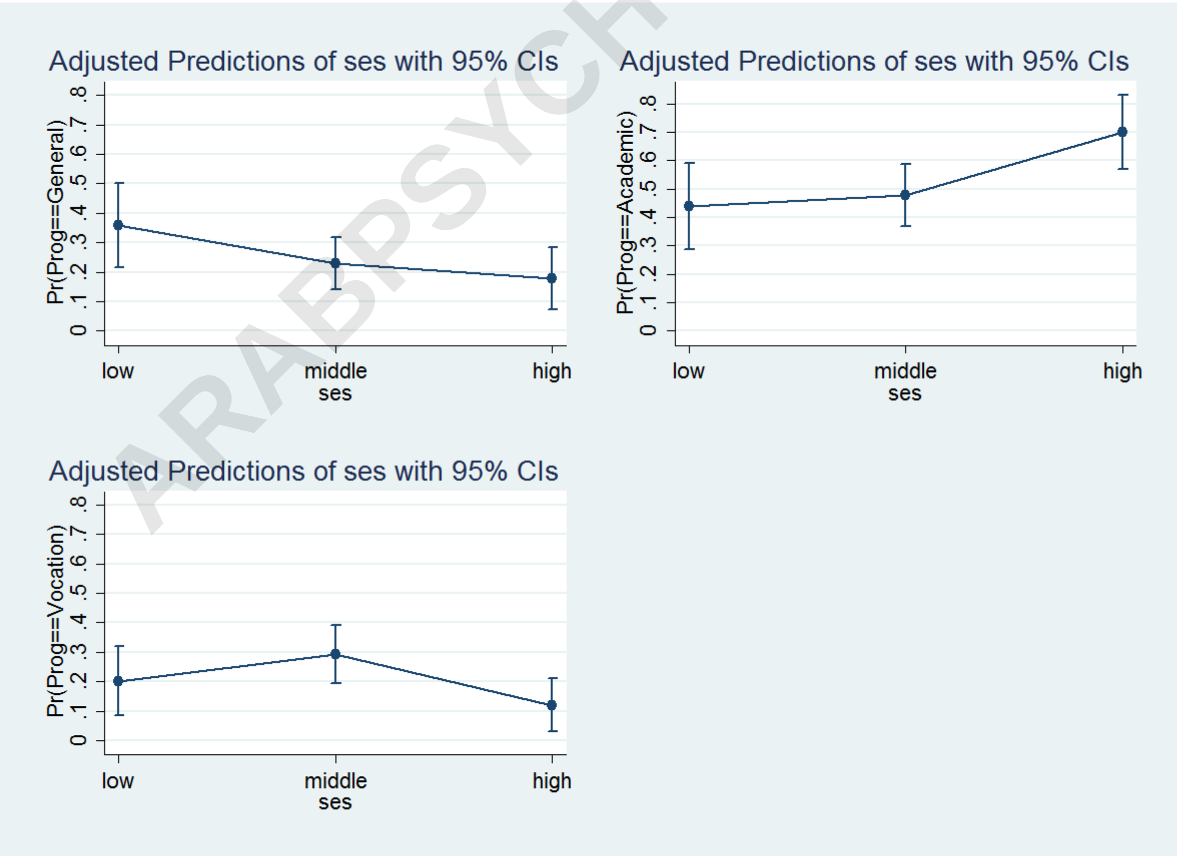
------------------------------------------------------------------------------

We can use the marginsplot command to plot predicted probabilities by ses for each category of prog. Plots created
by marginsplot are based on the last margins command run. Furthermore, we can combine the three marginsplots into one
graph to facilitate comparison using the graph combine command. As it is generated, each marginsplot must be given a name,
which will be used by graph combine. Additionally, we would
like the y-axes to have the same range, so we use the

**ycommon**

**option with graph combine .**

```
margins ses, atmeans predict(outcome(1))
marginsplot, name(general)
margins ses, atmeans predict(outcome(2))
marginsplot, name(academic)
margins ses, atmeans predict(outcome(3))
marginsplot, name(vocational)
graph combine general academic vocational, ycommon
```



**Another way to understand the model using the predicted probabilities is to**
**look at the averaged predicted probabilities for different values of the**
**continuous predictor variable write, averaging across levels of ses.**

**margins, at(write = (30(10) 70)) predict(outcome(1)) vsquish**

**Predictive margins Number of obs = 200**
**Model VCE : OIM**

**Expression : Pr(prog==general), predict(outcome(1))**
**1._at : write = 30**
**2._at : write = 40**
**3._at : write = 50**
**4._at : write = 60**
**5._at : write = 70**

**------------------------------------------------------------------------------**

**| Delta-method**
**| Margin Std. Err. z P>|z|**
**------------+----------------------------------------------------------------**
**_at |**

**1 | .2130954 .0774327 2.75 0.006 .0613302 .3648606**

**2 | .2569932 .0529761 4.85 0.000 .1531619 .3608245**

**3 | .2543008 .0336297 7.56 0.000 .1883878 .3202138**

**4 | .2057855 .0371536 5.54 0.000 .1329658 .2786052**

**5 | .1423089 .0481683 2.95 0.003 .0479007 .2367172**

**------------------------------------------------------------------------------**

**margins, at(write = (30(10) 70)) predict(outcome(2)) vsquish**

**Predictive margins Number of obs = 200**

**Model VCE : OIM**

**Expression : Pr(prog==academic), predict(outcome(2))**

**1._at : write = 30**

**2._at : write = 40**

**3._at : write = 50**

**4._at : write = 60**

**5._at : write = 70**

**------------------------------------------------------------------------------**

**| Delta-method**

**| Margin Std. Err. z P>|z|**

**-------------+----------------------------------------------------------------**

**_at |**

**1 | .1348408 .0525979 2.56 0.010 .0317507 .2379308**

**2 | .2808143 .0553213 5.08 0.000 .1723867 .389242**

**3 | .4773283 .0397591 12.01 0.000 .399402 .5552547**

**4 | .6680752 .0434689 15.37 0.000 .5828776 .7532727**

**5 | .8075124 .0545504 14.80 0.000 .7005956 .9144291**

**------------------------------------------------------------------------------**

**margins, at(write = (30(10) 70)) predict(outcome(3)) vsquish**

**Predictive margins Number of obs = 200**

**Model VCE : OIM**

**Expression : Pr(prog==vocation), predict(outcome(3))**

**1._at : write = 30**

**2._at : write = 40**

**3._at : write = 50**

**4._at : write = 60**

**5._at : write = 70**

**------------------------------------------------------------------------------**

**| Delta-method**

**| Margin Std. Err. z P>|z|**

**-------------+----------------------------------------------------------------**

**_at |**

**1 | .6520638 .0944041 6.91 0.000 .4670353 .8370924**

**2 | .4621925 .0614388 7.52 0.000 .3417747 .5826102**

**3 | .2683708 .0342932 7.83 0.000 .2011575 .3355842**

**4 | .1261393 .03019 4.18 0.000 .0669679 .1853107**

**5 | .0501787 .0216863 2.31 0.021 .0076744 .092683**

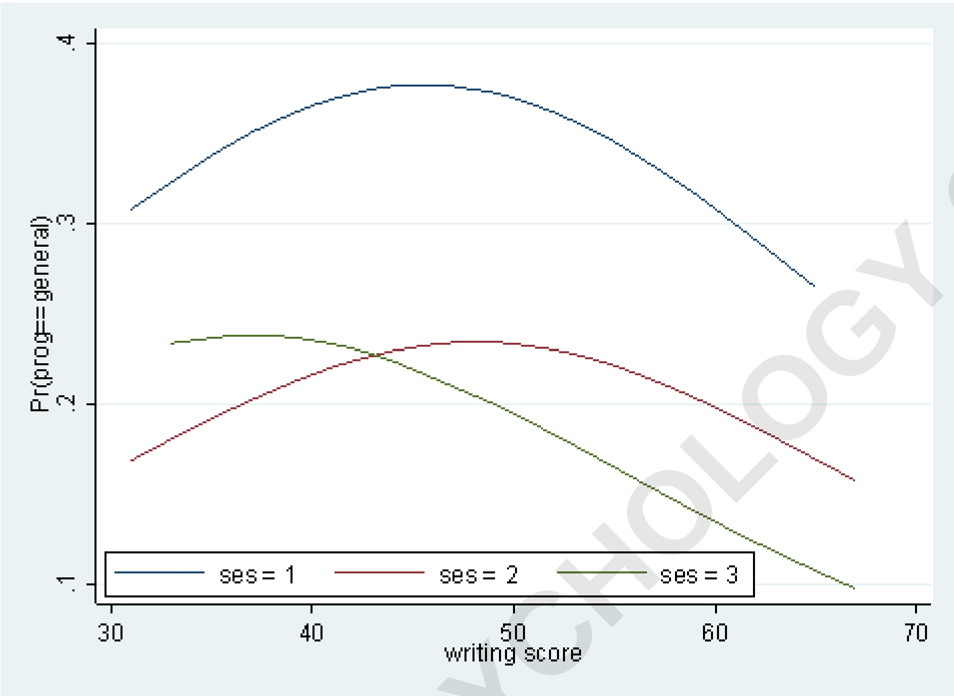
**------------------------------------------------------------------------------**

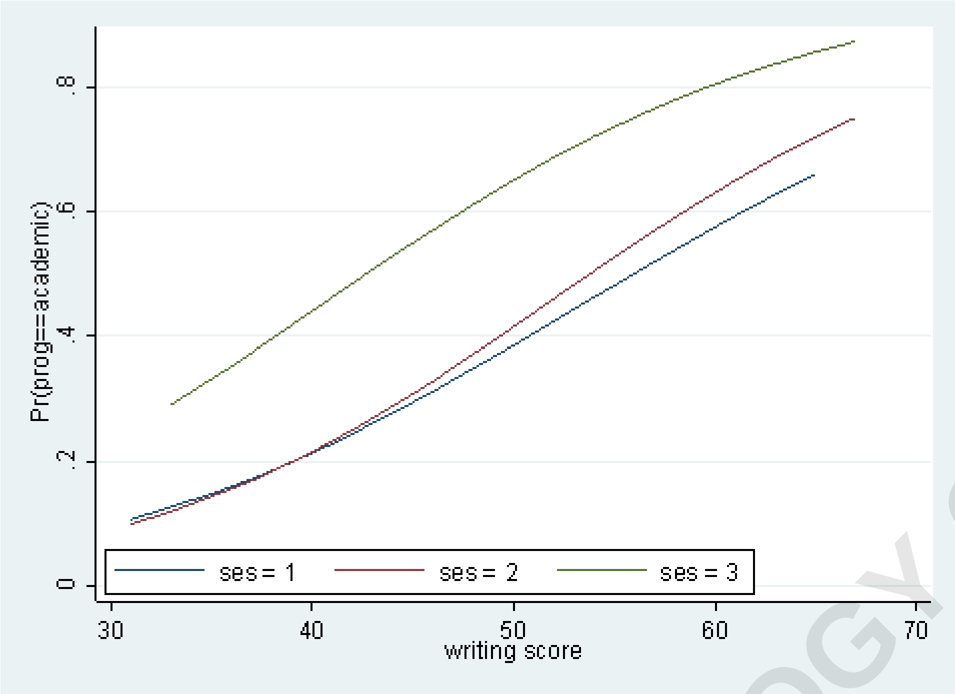
**Sometimes, a couple of plots can convey a good deal amount of information.**
**Below, we plot the predicted probabilities against the writing score by the**
**level of ses for different levels of the outcome variable.**

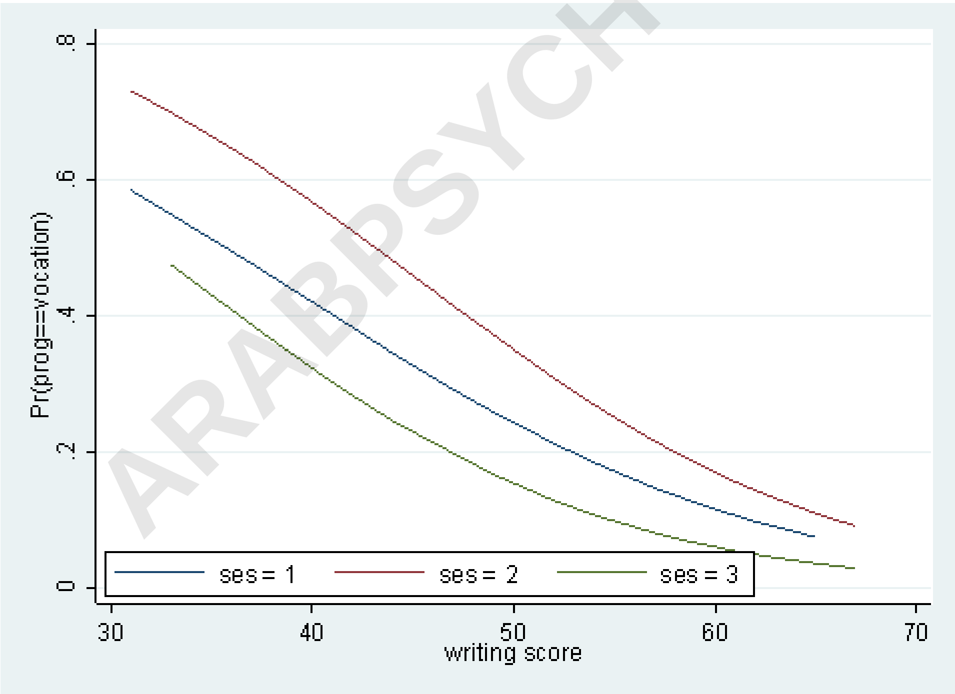
```
predict p1 p2 p3
sort write
twoway (line p1 write if ses ==1) (line p1 write if ses==2) (line p1 write if ses ==3), ///
legend(order(1 "ses = 1" 2 "ses = 2" 3 "ses = 3") ring(0) position(7) row(1))
twoway (line p2 write if ses ==1) (line p2 write if ses==2) (line p2 write if ses ==3), ///
legend(order(1 "ses = 1" 2 "ses = 2" 3 "ses = 3") ring(0) position(7) row(1))
twoway (line p3 write if ses ==1) (line p3 write if ses==2)
```

**(line p3 write if ses ==3), ///**

**legend(order(1 "ses = 1" 2 "ses = 2" 3 "ses = 3") ring(0) position(7) row(1))**






## We may also wish to see measures of how well our

**model fits. This can be particularly useful when comparing**
**competing models. The user-written command fitstat produces a**
**variety of fit statistics. You can find more information on fitstat and**
**download the program by using command**
**search fitstat in Stata (see**
**How can I use the search command to search for programs and get additional help?**
**for more information about using search).**

**fitstat**

**Measures of Fit for mlogit of prog**
**fit**
**Log-Lik Intercept Only: -204.097 Log-Lik Full Model: -179.982**
**D(185): 359.963 LR(6): 48.230**
**Prob > LR: 0.000**
**McFadden's R2: 0.118 McFadden's Adj R2: 0.045**
**ML (Cox-Snell) R2: 0.214 Cragg-Uhler(Nagelkerke) R2: 0.246**
**Count R2: 0.610 Adj Count R2: 0.179**

## AIC: 1.950 AIC*n: 389.963

## BIC: -620.225 BIC': -16.440

## BIC used by Stata: 402.350 AIC used by Stata: 375.963

### Things to consider

### See also

### References