How can negative binomial regression be utilized in Mplus for data analysis?

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Negative binomial regression is a statistical method utilized in Mplus for data analysis that is well-suited for count data with overdispersion, where the variance is larger than the mean. This method allows for the analysis of count data while accounting for the non-normal distribution and overdispersion, providing more accurate results than traditional linear regression models. By incorporating the negative binomial distribution into the regression model, Mplus can account for the excess zeros and higher variability in the data, providing a more robust analysis. This makes negative binomial regression a valuable tool in analyzing count data, such as number of events or occurrences, in a variety of research fields, including social sciences, epidemiology, and economics.

Negative Binomial Regression | Mplus Data Analysis Examples

Version info: Code for this page was tested in Mplus version 6.12.

Negative binomial regression is used to model count variables with overdispersion.

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 or

potential follow-up analyses.

Examples of negative binomial regression

Example 1. School administrators study the attendance behavior of high school juniors at two schools. Predictors of the number of days of absence include the type of program in which the student is enrolled and a standardized test in math.

Example 2. A health-related researcher is studying the number of hospital visits in past 12 months by senior citizens in a community based on the characteristics of the individuals and the types of health plans under which each one is covered.

Description of the data

We have attendance data on 314 high school juniors from two urban high schools in the file https://stats.idre.ucla.edu/wp-content/uploads/2016/02/nb_data.dat. The response variable of interest is days

absent, daysabs.
The variable math gives the standardized math score for
each student. The variable prog is a three-level nominal variable
indicating the type of instructional program in which the student is enrolled.
The variables p1, p2 and p3 are dummy-coded indicator variables
for prog.

Let's look at the data. It is always a good idea to start with descriptive
statistics.

Data:
File is g:daehttps://stats.idre.ucla.edu/wp-content/uploads/2016/02/nb_data.dat;
Variable:
Names are
id gender math daysabs prog p1 p2 p3;
Missing are all (-9999);
usevariables are id gender math daysabs prog p1 p2 p3;

analysis:

type = basic;

plot: type is plot1;

RESULTS FOR BASIC ANALYSIS

ESTIMATED SAMPLE STATISTICS

Means

ID GENDER MATH DAYSABS PROG

____________ ____________ ____________ ____________ ____________

1 1575.911 1.490 48.268 5.955 2.213

Means

P1 P2 P3

____________ ____________ ____________

1 0.127 0.532 0.341

Covariances

ID GENDER MATH DAYSABS PROG

____________ ____________ ____________ ____________ ____________

ID 251516.623

GENDER -27.319 0.250

MATH 4840.852 -0.227 641.202

DAYSABS -1193.221 -0.357 -41.966 49.361

PROG 165.742 0.004 3.895 -1.717 0.423

P1 -17.479 -0.005 -0.439 0.598 -0.155

P2 -130.784 0.007 -3.018 0.521 -0.113

P3 148.263 -0.002 3.457 -1.119 0.268

Covariances

P1 P2 P3

________ ________ ________

P1 0.111

P2 -0.068 0.249

P3 -0.043 -0.181 0.225

Correlations

ID GENDER MATH DAYSABS PROG

________ ________ ________ ________ ________

ID 1.000

GENDER -0.109 1.000

MATH 0.381 -0.018 1.000

DAYSABS -0.339 -0.102 -0.236 1.000

PROG 0.508 0.011 0.237 -0.376 1.000

P1 -0.105 -0.031 -0.052 0.255 -0.713

P2 -0.523 0.027 -0.239 0.148 -0.350

P3 0.624 -0.006 0.288 -0.336 0.870

Correlations

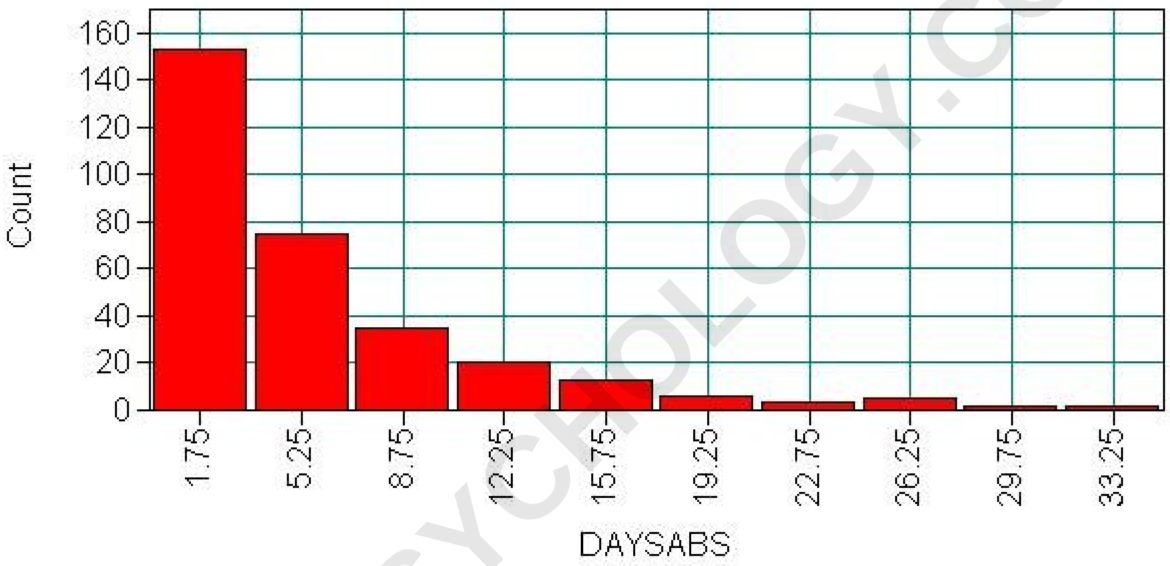
P1 P2 P3

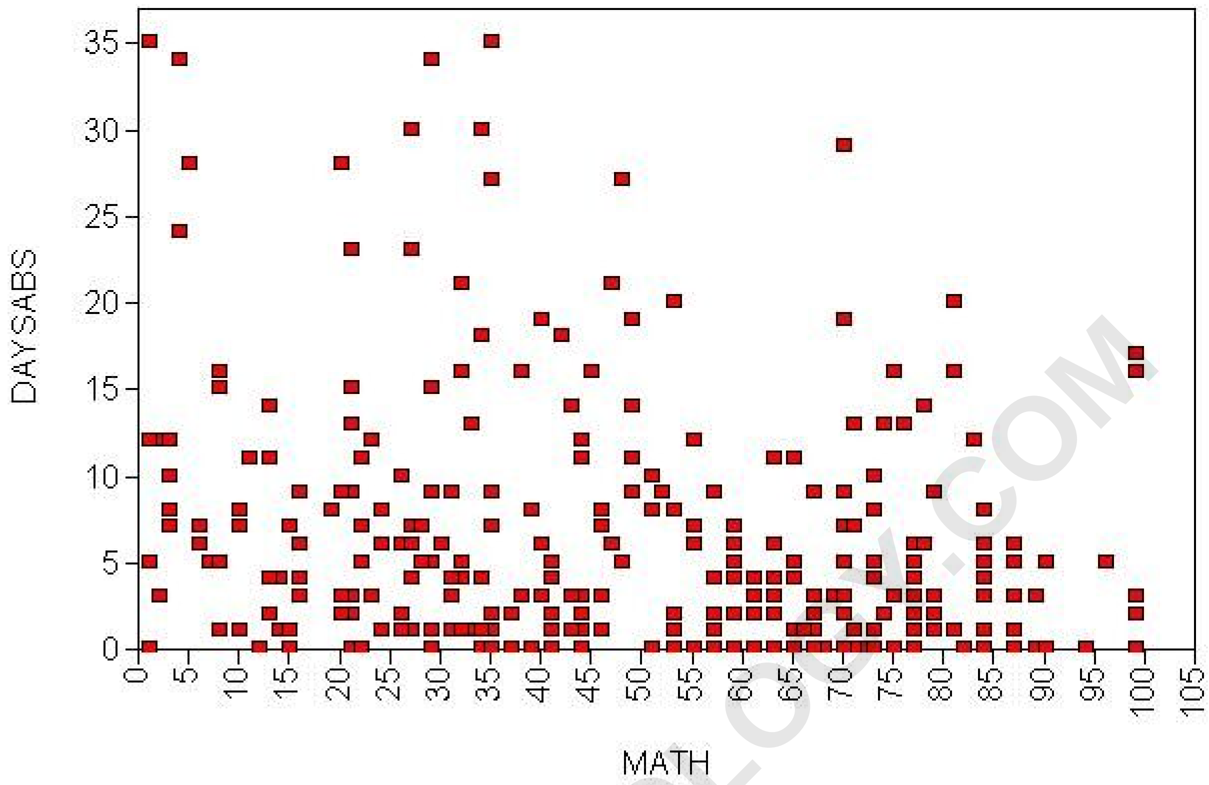
_____________ _____________ _____________

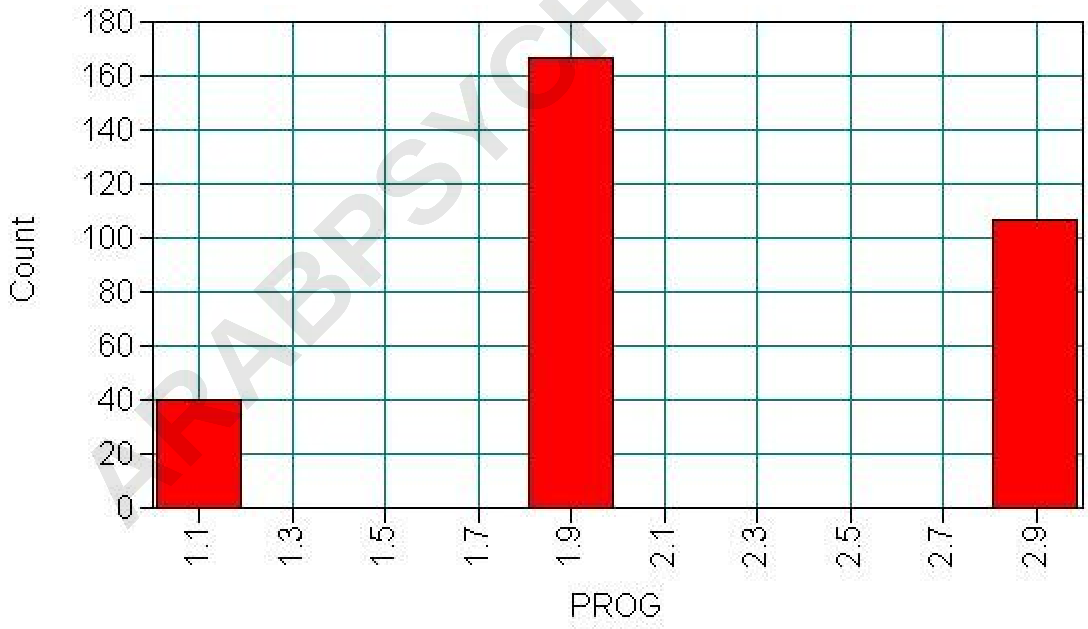
P1 1.000

P2 -0.407 1.000

P3 -0.275 -0.766 1.000




DAYSABS
MATH
0
5
10
15
20
25
30
35
40
45
50
55
60
65
70
75
80
85
90
95
100
105


Count
PROG
0
20
40
60
80
100
120
140
160
180
1.1
1.3
1.5
1.7
1.9
2.1
2.3
2.5
2.7
2.9

Analysis methods you might consider

Below is a list of some analysis methods you may have encountered. Some of the methods listed are quite reasonable, while others have either fallen out of favor or have limitations.

Negative binomial regression analysis

In the Mplus syntax below, we specify that the variables to be used in the negative binomial regression are daysabs, math, p2, p3, which will make prog=1 the reference group. We also specify that daysabs is a count variable, and we include (nb) to indicate that we want a negative binomial regression. (By default, Mplus would model this as a Poisson regression.) By default, Mplus uses restricted maximum likelihood (MLR), so robust standard errors would be given in the output. Here, the standard errors are calculated using maximum likelihood estimates by including the analysis: estimator = ml; block.

Data:

File is g:daehttps://stats.idre.ucla.edu/wp-content/uploads/2016/02/nb_data.dat;
Variable:
Names are
id gender math daysabs prog p1 p2 p3;
Missing are all (-9999);
usevariables are daysabs math p2 p3;
count is daysabs (nb);
model:
daysabs on math p2 p3;
analysis: estimator = ml;

MODEL FIT INFORMATION

Number of Free Parameters 5

Loglikelihood

H0 Value -865.629

Information Criteria

Akaike (AIC) 1741.258
Bayesian (BIC) 1760.005
Sample-Size Adjusted BIC 1744.146

(n* = (n + 2) / 24)

MODEL RESULTS

Two-Tailed

Estimate S.E. Est./S.E. P-Value

DAYSABS ON

MATH -0.006 0.003 -2.390 0.017

P2 -0.441 0.183 -2.414 0.016

P3 -1.279 0.202 -6.331 0.000

Intercepts

DAYSABS 2.615 0.196 13.319 0.000

Dispersion

DAYSABS 0.968 0.100 9.729 0.000

To determine if prog itself is statistically significant, we can
use the model test block to obtain the two degree-of-freedom test of this
variable. Additionally, we can get an estimate of the natural log of the
over-dispersion coefficient, alpha. If the alpha

coefficient is zero then the model is better estimated using a Poisson regression model.

Data:
File is g:daehttps://stats.idre.ucla.edu/wp-content/uploads/2016/02/nb_data.dat;
Variable:
Names are
id gender math daysabs prog p1 p2 p3;
Missing are all (-9999);
usevariables are daysabs math p2 p3;
count is daysabs (nb);
model:
daysabs on
math (a1)
p2 (a2)
p3 (a3);
model test:
a2 = 0;
a3 = 0;
analysis: estimator = ml;

MODEL FIT INFORMATION

<SOME OUTPUT OMITTED**>**

Wald Test of Parameter Constraints

Value 49.214
Degrees of Freedom 2
P-Value 0.0000

In the syntax above, some of the variables in the model are given labels.
These labels must be in parentheses and must be the last item listed on the line, so the model is broken up over several lines. We have given the label a2 to the indicator variable p2, and the label a3 to the indicator variable p3. Once we have assigned labels to the variables, we can use those labels in the model test block.
Setting both a2 and a3 to 0 allows us to get the two degree-of-freedom test of the variable prog. We can see that the

variable prog, as a whole, is statistically significant.

To obtain the results as incident rate ratios, we need to use the model
constraint block. Again, we use labels to refer to the variables
in the model. In the model constraint block, we use the new
statement to label the new parameters, which will be the exponentiated
parameters from the model.

Data:
File is g:daehttps://stats.idre.ucla.edu/wp-content/uploads/2016/02/nb_data.dat;
Variable:
Names are
id gender math daysabs prog p1 p2 p3;
Missing are all (-9999);
usevariables are daysabs math p2 p3;
count is daysabs (nb);
model:
daysabs on

math (a1)
p2 (a2)
p3 (a3);
model constraint:
new(math_exp p2_exp p3_exp);
math_exp = exp(a1);
p2_exp = exp(a2);
p3_exp = exp(a3);
analysis: estimator = ml;

MODEL FIT INFORMATION

Number of Free Parameters 5

Loglikelihood

H0 Value -865.629

Information Criteria

Akaike (AIC) 1741.258
Bayesian (BIC) 1760.005
Sample-Size Adjusted BIC 1744.146
(n* = (n + 2) / 24)

MODEL RESULTS

Two-Tailed

Estimate S.E. Est./S.E. P-Value

DAYSABS ON

MATH -0.006 0.003 -2.390 0.017

P2 -0.441 0.183 -2.414 0.016

P3 -1.279 0.202 -6.331 0.000

Intercepts

DAYSABS 2.615 0.196 13.319 0.000

Dispersion

DAYSABS 0.968 0.100 9.729 0.000

New/Additional Parameters

MATH_EXP 0.994 0.002 398.851 0.000

P2_EXP 0.644 0.117 5.477 0.000

P3_EXP 0.278 0.056 4.951 0.000

Things to consider

See also

References