What is Zero-truncated Negative Binomial Regression, and how is it used in Mplus data analysis?

Authored by

stats writer

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Zero-truncated Negative Binomial Regression is a statistical technique used in Mplus data analysis to model count data with excess zeros. It is a type of regression analysis that is suitable for analyzing data with a high proportion of zero values, where the traditional Negative Binomial Regression may not be appropriate. This method takes into account the truncation of the data at zero, which means it only models the counts above zero. It is often used in social science research to analyze data such as number of absences, number of hospitalizations, or number of criminal offenses. By incorporating the excess zeros, this method provides a more accurate estimation of the relationship between the independent variables and the count outcome. It is particularly useful in analyzing data with overdispersion, where the variance is greater than the mean. In summary, Zero-truncated Negative Binomial Regression is a specialized statistical tool that allows for the analysis of count data with a high proportion of zeros, providing researchers with a more precise understanding of the relationships between variables in their data.

Zero-truncated Negative Binomial Regression | Mplus Data Analysis Examples

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

Zero-truncated negative binomial regression is used to model count data for which the value zero cannot occur and when there is evidence of over dispersion .

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

verification, verification of assumptions, model diagnostics and potential follow-up analyses.

Examples of zero-truncated negative binomial

Example 1.

A study of the length of hospital stay, in days, as a function of age, kind of health insurance and whether or not the patient died while in the hospital. Length of hospital stay is recorded as a minimum of at least one day.

Example 2.

A study of the number of journal articles published by tenured faculty as a function of discipline (fine arts, science, social science, humanities, medical, etc). To get tenure faculty must publish, i.e., there are no tenured faculty with zero publications.

Example 3.

A study by the county traffic court on the number of

tickets received by teenagers
as predicted by school performance, amount of driver training and gender. Only individuals
who have received at least one citation are in the traffic court files.

Description of the data

Let's pursue Example 1 from above.

We have a hypothetical data file available here with 1,493 observations.
The variable describing length of hospital visit is stay.
The variable age gives the age group from 1 to 9 which will be treated as
interval in this example.
The variables hmo and died are binary indicator variables for HMO
insured patients and patients who died while in hospital, respectively.

Let's look at the data.

Data:
File is C:ztnb.dat;
Variable:

Names are
stay age hmo died;
Missing are all (-9999) ;
Analysis:
Type = basic ;
Plot:
Type = plot1;

ESTIMATED SAMPLE STATISTICS

Means
STAY AGE HMO DIED
________ ________ ________ ________
1 9.729 5.234 0.160 0.343

Covariances
STAY AGE HMO DIED
________ ________ ________ ________
STAY 66.100
AGE -0.615 2.785
HMO -0.169 -0.006 0.134
DIED -0.447 0.121 0.000 0.225

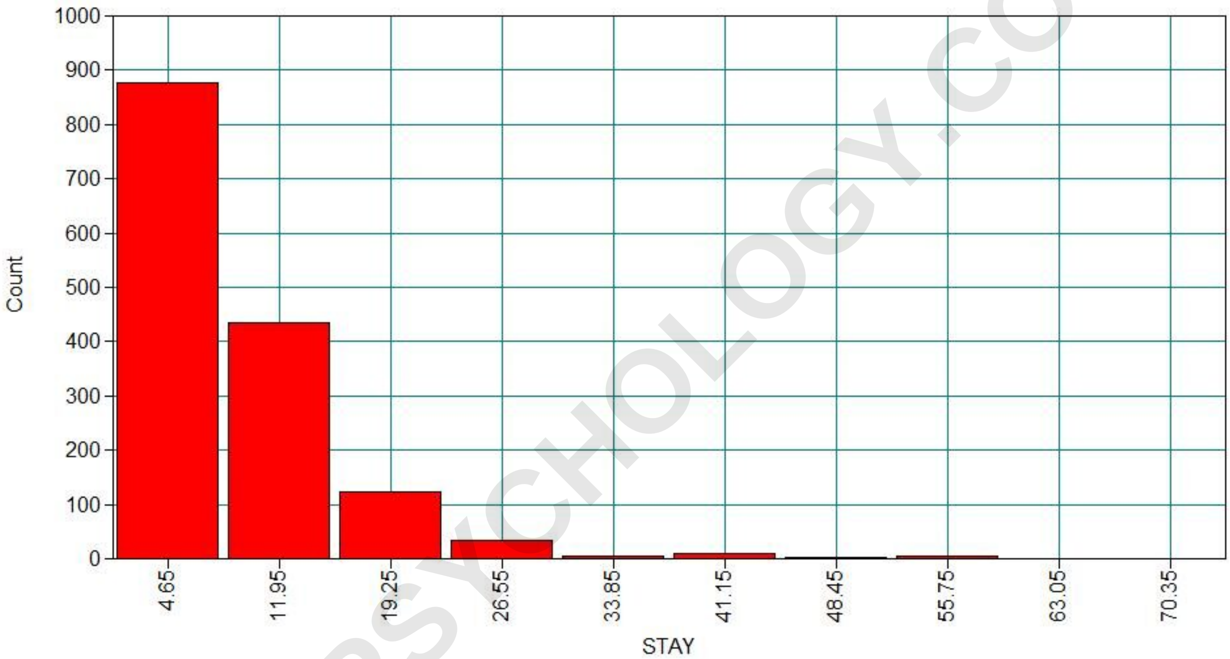
Correlations
STAY AGE HMO DIED

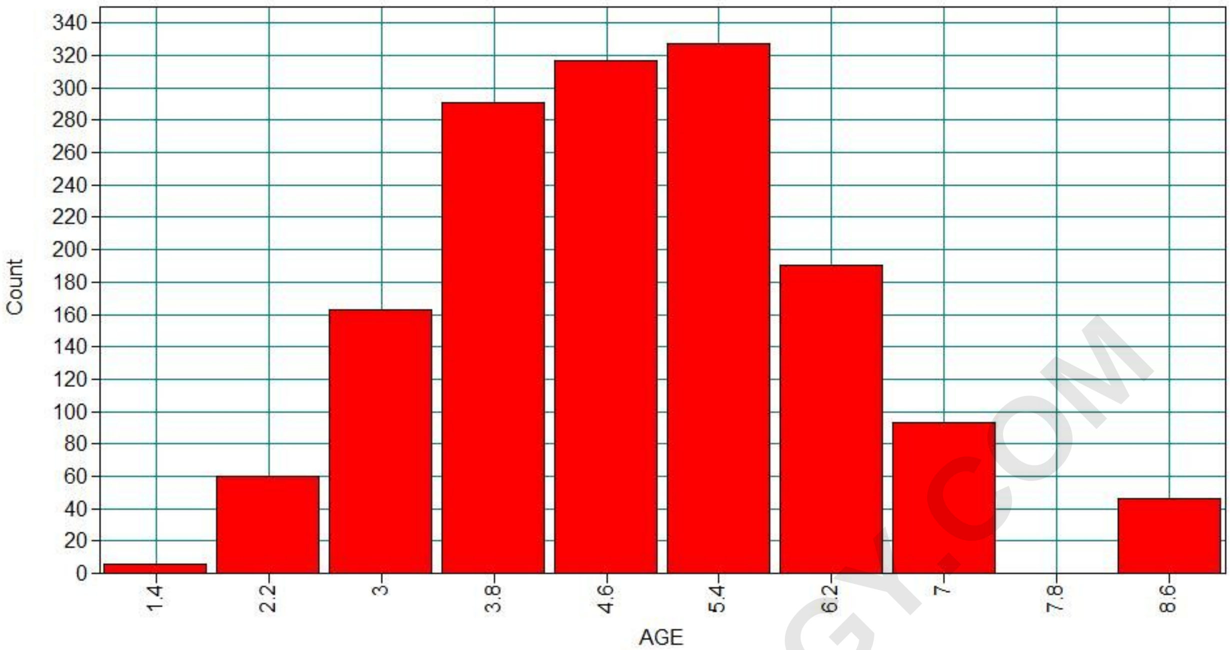
STAY 1.000

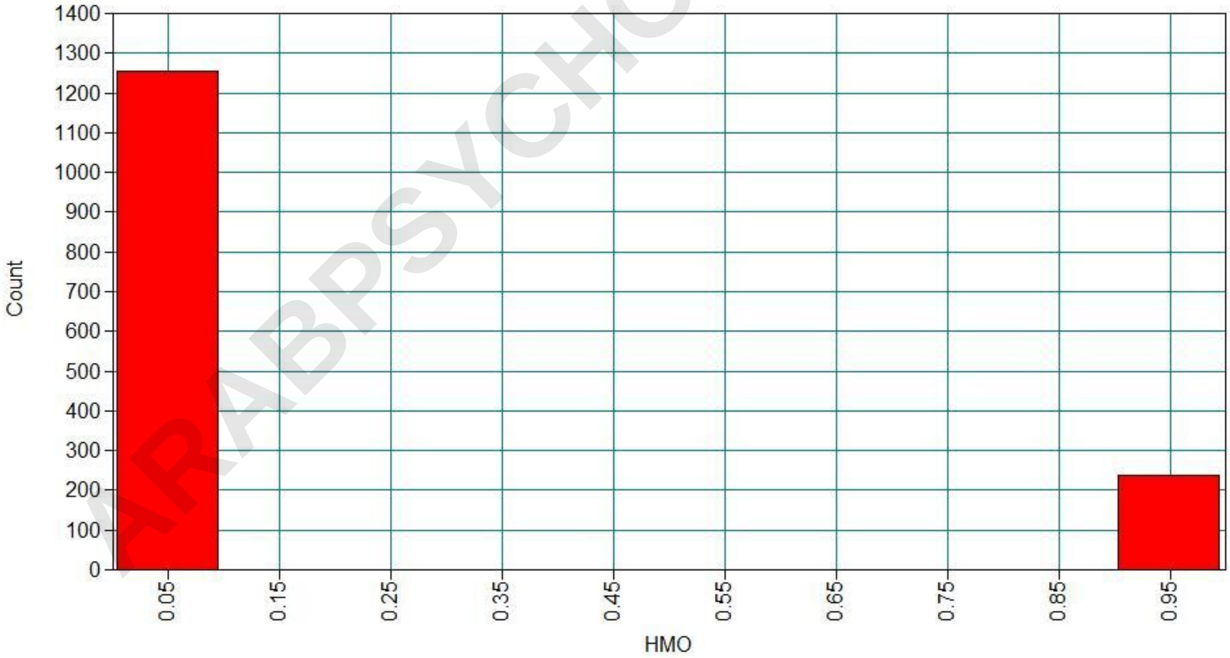
AGE -0.045 1.000

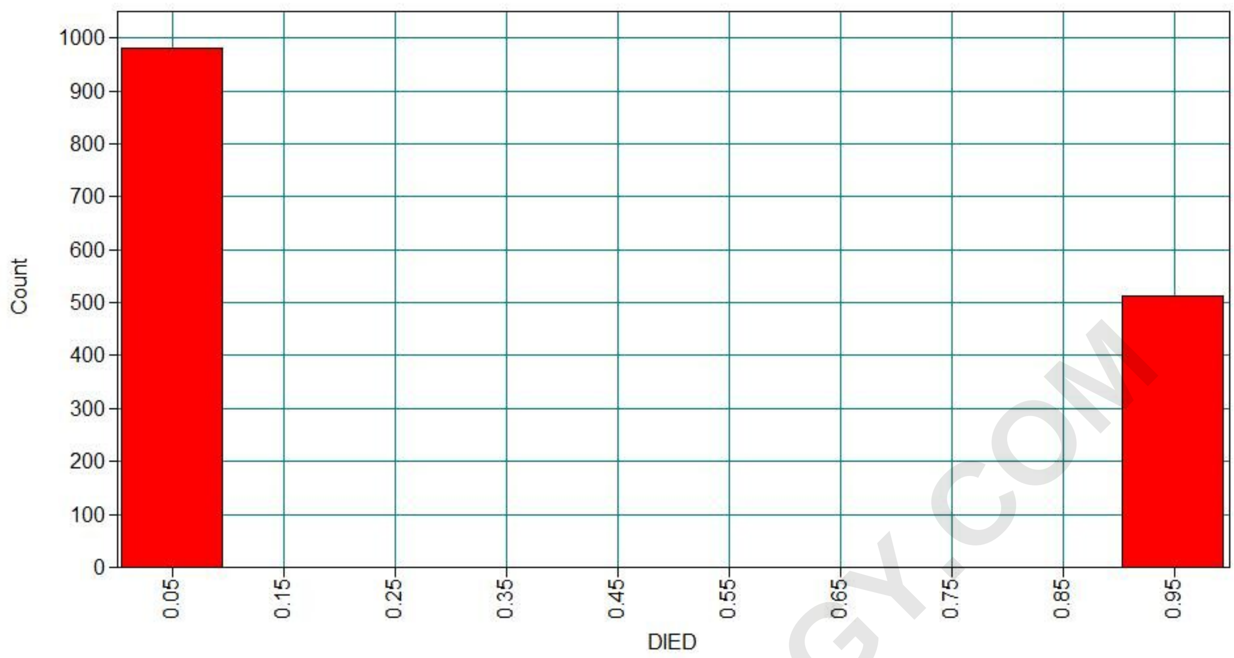
HMO -0.057 -0.010 1.000

DIED -0.116 0.152 0.000 1.000




Count
340
320
300
280
260
240
220
200
180
160
140
120
100
80
60
40
20
0
1.4
2.2
3
3.8
4.6
5.4
6.2
7
7.8
8.6
AGE


Count
1400
1300
1200
1100
1000
900
800
700
600
500
400
300
200
100
0
0.05
0.15
0.25
0.35
0.45
0.55
0.65
0.75
0.85
0.95
HMO



Analysis methods you might consider

Before we show how you can analyze these data with a zero-truncated negative binomial analysis, let's consider some other methods that you might use.

Zero-trunacated negative binomial regression

In the syntax below, we have indicated that stay is a count variable by using the count statement. The (nbt) option is used to indicate 2 things: that we are modeling our

count variable with a negative binomial distribution, and that we are specifying a zero-truncated model. Without the (t) option we would be estimating a negative binomial model without zero-truncation. Also, we do not need a usevariables statement because we are using all of the variables in the data set in the current model. We have omitted the missing statement because we have no missing data in this data set. The default estimation method is MLR - maximum likelihood parameter estimates with standard errors and a chi-square test statistic that are robust to non-normality and non-independence of observations. The MLR standard errors are computed using a sandwich estimator. This is what we generally call robust standard errors. To get the "regular" standard errors, we use the estimator = ml on the analysis statement. (In the next example, we

will
omit the analysis statement and obtain the robust standard errors.)
Our regression equations is specified in the model statement: we are predicting
length of stay using age, hmo status and whether the patient died.

Data:
File is C:ztnb.dat ;
Variable:
Names = stay age hmo died;
Count = stay(nbt);
Model:
stay on age hmo died;

MODEL FIT INFORMATION

Number of Free Parameters 5

Loglikelihood

H0 Value -4755.280
H0 Scaling Correction Factor 1.156
for MLR

Information Criteria

Akaike (AIC) 9520.559
Bayesian (BIC) 9547.102
Sample-Size Adjusted BIC 9531.218
(n* = (n + 2) / 24)

MODEL RESULTS

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

STAY ON
AGE -0.016 0.013 -1.194 0.233
HMO -0.147 0.057 -2.571 0.010
DIED -0.218 0.053 -4.142 0.000

Intercepts
STAY 2.408 0.075 32.039 0.000

Dispersion
STAY 0.566 0.037 15.316 0.000

In the MODEL FIT INFORMATION portion of the output, you will find the log likelihood for the final model as well as a number of fit

statistics. In the
MODEL RESULTS section of the output you will find the negative binomial
regression coefficients (estimates) for each of the variables, standard errors
and the ratio of the estimate to its standard error. This can be used as a
Z test, where values greater than 2 are considered to be statistically
significant. We see that hmo and died but not age are significant predictors of stay. Thus, for example, for patients who
use HMO services compared to those who do not, the log count of days stayed is
about 0.147 less.

Now let's rerun the model without the analysis: estimator = ml statement in order to obtain robust standard errors.

Data:
File is C:ztnb.dat ;
Variable:
Names = stay age hmo died;

Missing = all (-9999) ;

Count = stay(nbt);

Model:

stay on age hmo died;

Analysis:

estimator = ml;

MODEL RESULTS

Two-Tailed

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

STAY ON

AGE -0.016 0.013 -1.197 0.231

HMO -0.147 0.059 -2.483 0.013

DIED -0.218 0.046 -4.718 0.000

Intercepts

STAY 2.408 0.072 33.457 0.000

Dispersion

STAY 0.566 0.031 18.132 0.000

Robust standard errors tend to be larger than "regular" standard errors,

though not always as we see for the variable age. The results changed very little when using regular standard errors.

Things to consider

References