What is the concept behind Zero-inflated Poisson Regression in Stata Data Analysis?

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Zero-inflated Poisson Regression is a statistical method used in Stata Data Analysis to model count data with excessive zeros. It combines two models, one for the excess zeros and the other for the count data, to account for the excessive zeros and provide more accurate predictions. This concept is based on the idea that the excessive zeros in the data are due to a separate process or mechanism that needs to be accounted for in addition to the count data model. By incorporating this concept, Zero-inflated Poisson Regression allows for a more comprehensive and accurate analysis of count data with excessive zeros. This method is commonly used in various fields such as healthcare, economics, and social sciences to better understand and predict phenomena that involve count data with excessive zeros.

Zero-inflated Poisson Regression | Stata Data Analysis Examples

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

Zero-inflated poisson regression is used to model count data that has an excess of zero counts.
Further, theory suggests that the excess zeros
are generated by a separate process from the count values and that the excess zeros can
be modeled independently. Thus, the zip model has two parts, a
poisson count model and the logit model
for predicting excess zeros. You may want to review these Data Analysis Example pages,
Poisson Regression and
Logit Regression.

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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-inflated Poisson regression

Example 1.

School administrators study the attendance behavior of high school juniors over one semester at two schools. Attendance is measured by number of days of absent and is predicted by gender of the student and standardized test scores in math and language arts. Many students have no absences during the semester.

Example 2.

The state wildlife biologists want to model how many fish are being caught by fishermen

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at a state park. Visitors are asked whether or not they have a camper, how many people were in the group, were there children in the group and how many fish were caught. Some visitors do not fish, but there is no data on whether a person fished or not. Some visitors who did fish did not catch any fish so there are excess zeros in the data because of the people that did not fish.

Description of the data

Let's pursue Example 2 from above.

We have data on 250 groups that went to a park. Each group was questioned about how many fish they caught (count), how many children were in the group (child), how many people were in the group (persons), and whether or not they brought a camper to the park (camper).

In addition to predicting the number of fish caught, there is interest in

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predicting the existence of excess zeros, i.e. the zeroes that were not simply a
result of bad luck fishing. We will use the variables child, persons, and
camper in our model. Let's look at the data.

use http://www.stata-press.com/data/r10/fish, clear

summarize count child persons camper

Variable | Obs Mean Std. Dev. Min Max
-------------+--
count | 250 3.296 11.63503 0 149
child | 250 .684 .8503153 0 3
persons | 250 2.528 1.11273 1 4
camper | 250 .588 .4931824 0 1

histogram count, discrete freq

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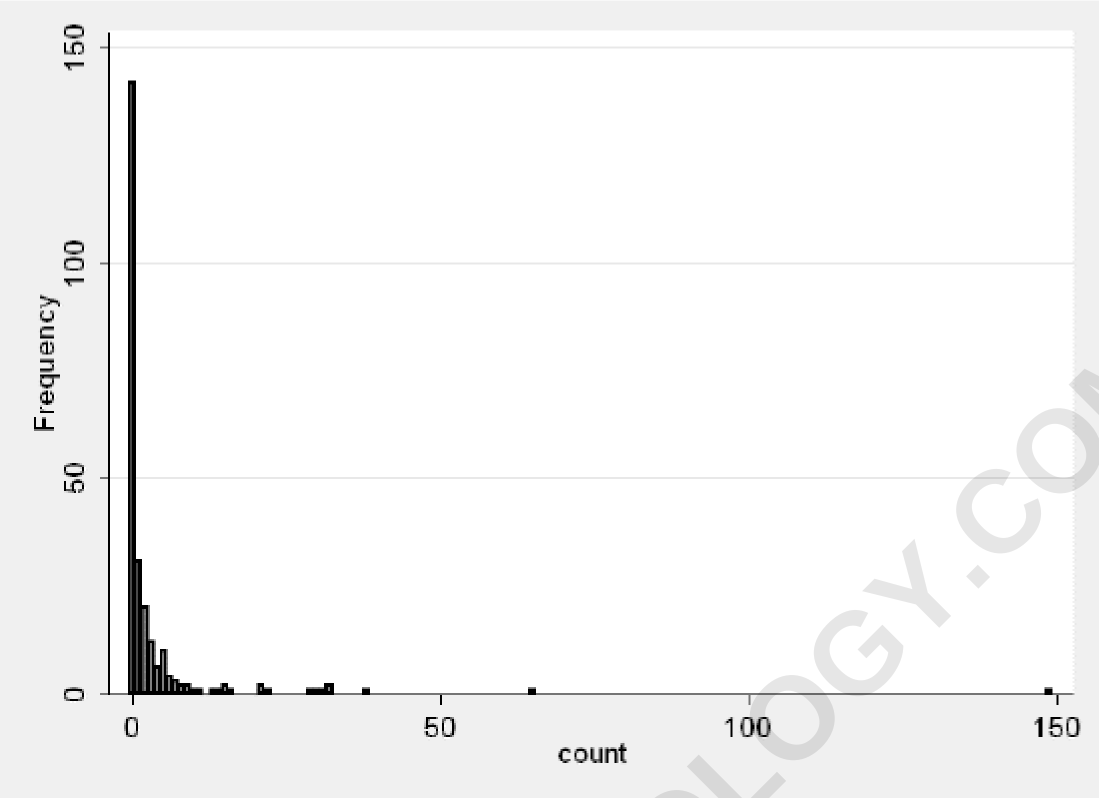

tab1 child persons camper

-> tabulation of child

child | Freq. Percent Cum.

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

0 | 132 52.80 52.80

1 | 75 30.00 82.80

2 | 33 13.20 96.00

3 | 10 4.00 100.00

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

Total | 250 100.00

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-> tabulation of persons

persons | Freq. Percent Cum.

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

1 | 57 22.80 22.80

2 | 70 28.00 50.80

3 | 57 22.80 73.60

4 | 66 26.40 100.00

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

Total | 250 100.00

-> tabulation of camper

camper | Freq. Percent Cum.

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

0 | 103 41.20 41.20

1 | 147 58.80 100.00

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

Total | 250 100.00

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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.

Zero-inflated Poisson regression

We will run the zip command with child and camper as predictors of the counts, persons as the predictor of the excess zeros.

zip count child camper, inflate(persons)

Fitting constant-only model:

Iteration 0: log likelihood = -1347.807
Iteration 1: log likelihood = -1315.5343
Iteration 2: log likelihood = -1126.3689
Iteration 3: log likelihood = -1125.5358
Iteration 4: log likelihood = -1125.5357
Iteration 5: log likelihood = -1125.5357

Fitting full model:

Iteration 0: log likelihood = -1125.5357
Iteration 1: log likelihood = -1044.8553
Iteration 2: log likelihood = -1031.8733
Iteration 3: log likelihood = -1031.6089

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Iteration 4: log likelihood = -1031.6084

Iteration 5: log likelihood = -1031.6084

Zero-inflated Poisson regression Number of obs = 250

Nonzero obs = 108

Zero obs = 142

Inflation model = logit LR chi2(2) = 187.85

Log likelihood = -1031.608 Prob > chi2 = 0.0000

--

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

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

count |

child | -1.042838 .0999883 -10.43 0.000 -1.238812 -.846865

1.camper | .8340222 .0936268 8.91 0.000 .650517 1.017527

_cons | 1.597889 .0855382 18.68 0.000 1.430237 1.76554

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

inflate |

persons | -.5643472 .1629638 -3.46 0.001 -.8837503 -.244944

_cons | 1.297439 .3738522 3.47 0.001 .5647022 2.030176

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The output looks very much like the output from an OLS regression:

Cameron and Trivedi (2009) recommend robust standard errors for Poisson models.
We will rerun the model with the vce(robust) option.

zip count child i.camper, inflate(persons) vce(robust)

Fitting constant-only model:

Iteration 0: log pseudolikelihood = -1347.807
Iteration 1: log pseudolikelihood = -1315.5343
Iteration 2: log pseudolikelihood = -1126.3689
Iteration 3: log pseudolikelihood = -1125.5358
Iteration 4: log pseudolikelihood = -1125.5357
Iteration 5: log pseudolikelihood = -1125.5357

Fitting full model:

Iteration 0: log pseudolikelihood = -1125.5357
Iteration 1: log pseudolikelihood = -1044.8553
Iteration 2: log pseudolikelihood = -1031.8733
Iteration 3: log pseudolikelihood = -1031.6089

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Iteration 4: log pseudolikelihood = -1031.6084

Iteration 5: log pseudolikelihood = -1031.6084

Zero-inflated Poisson regression Number of obs = 250

Nonzero obs = 108

Zero obs = 142

Inflation model = logit Wald chi2(2) = 7.25

Log pseudolikelihood = -1031.608 Prob > chi2 = 0.0266

--

| Robust

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

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

count |

child | -1.042838 .3893772 -2.68 0.007 -1.806004 -.2796731

1.camper | .8340222 .4076029 2.05 0.041 .0351352 1.632909

_cons | 1.597889 .2934631 5.44 0.000 1.022711 2.173066

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

inflate |

persons | -.5643472 .2888849 -1.95 0.051 -1.130551 .0018567

_cons | 1.297439 .493986 2.63 0.009 .3292445 2.265634

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Now we can move on to the specifics of the individual results.

We can use the margins to help understand our model. We will
first compute the expected counts for the categorical variable camper while holding the
continuous variable child at its mean value using the atmeans option.

margins camper, atmeans

Adjusted predictions Number of obs = 250
Model VCE : Robust

Expression : Predicted number of events, predict()
at : child = .684 (mean)
0.camper = .412 (mean)
1.camper = .588 (mean)
persons = 2.528 (mean)

--

| Delta-method

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

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

camper |

0 | 1.289132 .4393168 2.93 0.003 .4280866 2.150177

1 | 2.968305 .619339 4.79 0.000 1.754423 4.182187

The expected count for the number of fish caught by non-campers is 1.289 while for campers it is 2.968 at the means of child and persons.

Using the dydx option computes the difference in expected counts between camper = 0 and camper = 1 while still holding child at its mean of .684 and persons at its mean of 2.528.

margins, dydx(camper) atmeans

Conditional marginal effects Number of obs = 250

Model VCE : Robust

Expression : Predicted number of events, predict()

dy/dx w.r.t. : 1.camper

at : child = .684 (mean)

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0.camper = .412 (mean)
1.camper = .588 (mean)
persons = 2.528 (mean)

--

| Delta-method
| dy/dx Std. Err. z P>|z|
-------------+--
1.camper | 1.679173 .7754611 2.17 0.030 .1592975 3.199049
--
Note: dy/dx for factor levels is the discrete change from the base level.

The difference in the number of fish caught by campers and non-campers is 1.679, which is statistically significant.

One last margins command will give the expected counts for values of child from zero to three at both levels of camper.

margins, at(child=(0(1)3) camper=(0/1)) vsquish

Predictive margins Number of obs = 250

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Model VCE : Robust

Expression : Predicted number of events, predict()

1._at : child = 0

camper = 0

2._at : child = 0

camper = 1

3._at : child = 1

camper = 0

4._at : child = 1

camper = 1

5._at : child = 2

camper = 0

6._at : child = 2

camper = 1

7._at : child = 3

camper = 0

8._at : child = 3

camper = 1

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--

| Delta-method

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

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

_at |

1 | 2.616441 .6470522 4.04 0.000 1.348242 3.88464

2 | 6.024516 2.159288 2.79 0.005 1.79239 10.25664

3 | .922172 .4142303 2.23 0.026 .1102954 1.734048

4 | 2.123358 .4771534 4.45 0.000 1.188154 3.058561

5 | .3250221 .2611556 1.24 0.213 -.1868335 .8368777

6 | .7483834 .3929987 1.90 0.057 -.0218798 1.518647

7 | .114555 .1351887 0.85 0.397 -.1504101 .37952

8 | .2637699 .2365495 1.12 0.265 -.1998587 .7273984

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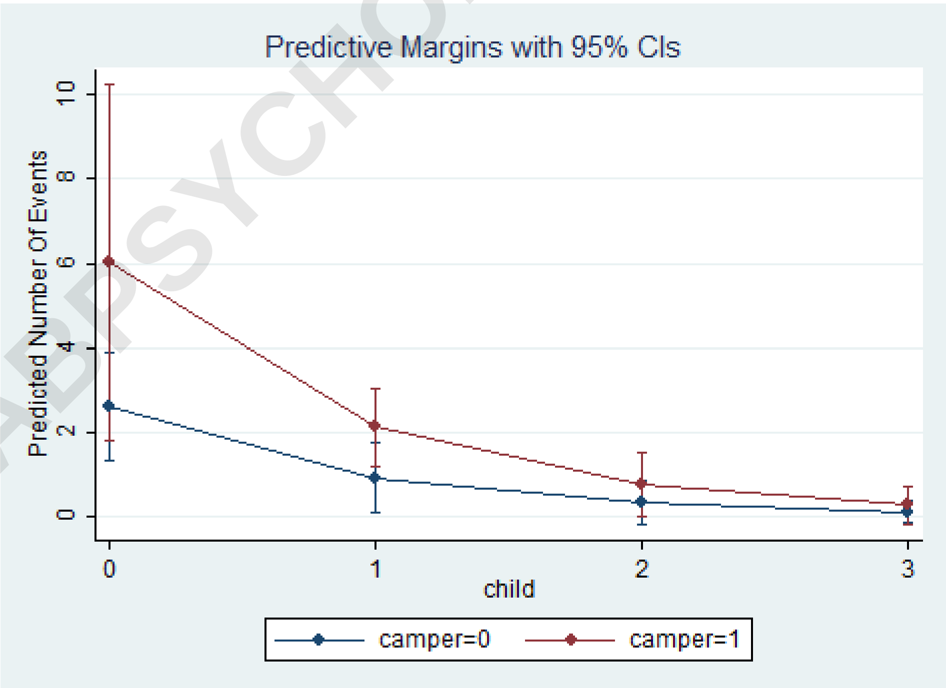

marginsplot

The expected number of fish caught goes down as the number of children goes up

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for both people with and without campers.

A number of model fit indicators are available using the fitstat command, which is part of the spostado utilities by J. Scott Long and Jeremy Freese (search spostado).

fitstat

Measures of Fit for zip of count

Log-Lik Intercept Only: -1127.023 Log-Lik Full Model: -1031.608
D(244): 2063.217 LR(4): 190.829
Prob > LR: 0.000
McFadden's R2: 0.085 McFadden's Adj R2: 0.079
ML (Cox-Snell) R2: 0.534 Cragg-Uhler(Nagelkerke) R2: 0.534
AIC: 8.301 AIC*n: 2075.217
BIC: 715.980 BIC': -168.743
BIC used by Stata: 2090.824 AIC used by Stata: 2073.217

Things to consider

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See also

References

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