**Description**

`zinb` fits a zero-inflated negative binomial (ZINB) model to overdispersed count data with excess zero counts. The ZINB model assumes that the excess zero counts come from a logit or probit model and the remaining counts come from a negative binomial model.

**Quick start**

Zero-inflated negative binomial model of `y` on `x1` and `x2` with inflation modeled using `x3`

```
zinb y x1 x2, inflate(x3)
```

And conduct likelihood-ratio test against ZIP model

```
zinb y x1 x2, inflate(x3) zip
```

Use a probit model instead of a logit model to predict excess zeros

```
zinb y x1 x2, inflate(x3) probit
```

**Menu**

Statistics > Count outcomes > Zero-inflated negative binomial regression
Syntax

\texttt{zinb depvar [indepvars] [if] [in] [weight],}

\texttt{inflate(varlist[, offset(varname) ] | _cons) [options]}

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\texttt{* inflate(varlist[, offset(varname) ] | _cons) is required.}
\texttt{indepvars and varlist may contain factor variables; see [U] 11.4.3 Factor variables.}
\texttt{bayes, bootstrap, by, fp, jackknife, rolling, statsby, and svy are allowed; see [U] 11.1.10 Prefix commands.}
\texttt{For more details, see [BAYES] bayes: zinb.}
\texttt{Weights are not allowed with the bootstrap prefix; see [R] bootstrap.}
\texttt{vce(), zip, and weights are not allowed with the svy prefix; see [SVY] svy.}
\texttt{fweights, iweights, and pweights are allowed; see [U] 11.1.6 weight.}
\texttt{collinear and coeflegend do not appear in the dialog box.}
\texttt{See [U] 20 Estimation and postestimation commands for more capabilities of estimation commands.}
Options

Model

\texttt{inflate(varlist[, offset(varname)] | \_cons)} specifies the equation that determines whether the observed count is zero. Conceptually, omitting \texttt{inflate()} would be equivalent to fitting the model with \texttt{nbreg}.

\texttt{inflate(varlist[, offset(varname)]]} specifies the variables in the equation. You may optionally include an offset for this \texttt{varlist}.

\texttt{inflate(_cons)} specifies that the equation determining whether the count is zero contains only an intercept. To run a zero-inflated model of \texttt{depvar} with only an intercept in both equations, type \texttt{zinb depvar, inflate(_cons)}.

\texttt{noconstant, exposure(varname\_e), offset(varname\_o), constraints(constraints)}; see [R] Estimation options.

\texttt{probit} requests that a probit, instead of logit, model be used to characterize the excess zeros in the data.

SE/Robust

\texttt{vce(vcetype)} specifies the type of standard error reported, which includes types that are derived from asymptotic theory (\texttt{oim, opg}), that are robust to some kinds of misspecification (\texttt{robust}), that allow for intragroup correlation (\texttt{cluster clustvar}), and that use bootstrap or jackknife methods (\texttt{bootstrap, jackknife}); see [R] vce option.

Reporting

\texttt{level(#)}; see [R] Estimation options.

\texttt{irr} reports estimated coefficients transformed to incidence-rate ratios, that is, $e^{\beta_i}$ rather than $\beta_i$. Standard errors and confidence intervals are similarly transformed. This option affects how results are displayed, not how they are estimated or stored. \texttt{irr} may be specified at estimation or when replaying previously estimated results.

\texttt{zip} requests that a likelihood-ratio test comparing the ZINB model with the zero-inflated Poisson model be included in the output.

\texttt{nocnsreport}; see [R] Estimation options.

\texttt{display_options: noci, nopvalues, nomitted, vsquish, noemptycells, baselevels, allbaselevels, nolabels, fvwrap(#), fvwrapon(style), cformat(\%fmt), pformat(\%fmt), sformat(\%fmt), and nolstretch}; see [R] Estimation options.

Maximization

\texttt{maximize_options: difficult, technique(algorithm\_spec), iterate(#), [no]log, trace, gradient, showstep, hessian, showtolerance, tolerance(#), \_\_tolerance(#), nrtolerance(#), nonrtolerance, and from(init\_specs)}; see [R] Maximize. These options are seldom used.

Setting the optimization type to \texttt{technique(bhhh)} resets the default \texttt{vcetype} to \texttt{vce(opg)}.

The following options are available with \texttt{zinb} but are not shown in the dialog box:

\texttt{collinear, coeflegend}; see [R] Estimation options.
Remarks and examples

Zero-inflated negative binomial (ZINB) models are used to model count data that have a higher fraction of zeros than is likely to be generated by a standard negative binomial model. To account for excess zeros, ZINB models assume that these excess zeros come from a model other than the negative binomial model. A zero that comes from this other model is known as a “degenerate zero”.

The negative binomial overdispersion parameter, \( \alpha \), differentiates the ZINB model from the zero-inflated Poisson (ZIP) model (see `[R] zip`). Here, overdispersion refers to the fact that the negative binomial variance is greater than its mean, whereas the Poisson variance is equal to its mean. Thus, values of \( \alpha > 1 \) indicate overdispersion. The larger the \( \alpha \), the greater the negative binomial variance. See Methods and formulas in `[R] nbreg` for further discussion of negative binomial overdispersion.

The zinb command fits ZINB models and provides two choices for modeling the excess zeros: the default logit function or, when the `probit` option is specified, the probit function. Both functions are symmetric about zero, but the logistic function has more area under the tails.


Example 1: Fitting a ZINB model

In example 1 of `[R] zip`, we fit a zero-inflated Poisson model using the `zip` command to the fictional data on the number of fish caught by visitors to a national park. Let’s fit a ZINB model to these data.

Just like with `zip`, we use the required option `inflate()` to model whether a visitor fishes as a function of the number of accompanying children (`child`) and whether the visitor is camping (`camper`). Next, we assume the response variable, `count`, depends on whether the visitor used a live bait (`livebait`) and the number of persons in the party (`persons`), which includes the visitor plus other adults and children.
. use https://www.stata-press.com/data/r16/fish
(Fictional fishing data)
. zinb count persons livebait, inflate(child camper)

Fitting constant-only model:
Iteration 0:  log likelihood = -519.33992
Iteration 1:  log likelihood = -451.38662
Iteration 2:  log likelihood = -444.49118
Iteration 3:  log likelihood = -442.96272
Iteration 4:  log likelihood = -442.71065
Iteration 5:  log likelihood = -442.66718
Iteration 6:  log likelihood = -442.6631
Iteration 7:  log likelihood = -442.66299
Iteration 8:  log likelihood = -442.66299

Fitting full model:
Iteration 0:  log likelihood = -442.66299 (not concave)
Iteration 1:  log likelihood = -432.83107 (not concave)
Iteration 2:  log likelihood = -426.32934
Iteration 3:  log likelihood = -413.75019
Iteration 4:  log likelihood = -403.09586
Iteration 5:  log likelihood = -401.56013
Iteration 6:  log likelihood = -401.54781
Iteration 7:  log likelihood = -401.54776
Iteration 8:  log likelihood = -401.54776

Zero-inflated negative binomial regression
Number of obs = 250
Nonzero obs = 108
Zero obs = 142

Inflation model = logit
LR chi2(2) = 82.23
Log likelihood = -401.5478
Prob > chi2 = 0.0000

| count     | Coef.    | Std. Err. | z     | P>|z|   | [95% Conf. Interval] |
|-----------|----------|-----------|-------|------|---------------------|
| count     |          |           |       |      |                     |
| persons   | .9742984 | .1034938  | 9.41  | 0.000| .7714543 1.177142   |
| livebait  | 1.557523 | .4124424  | 3.78  | 0.000| .7491503 2.365895   |
| _cons     | -2.730064| .476953   | -5.72 | 0.000| -3.664874 -1.795253 |

| inflate   |          |           |       |      |                     |
| child     | 3.185999 | .7468551  | 4.27  | 0.000| 1.72219 4.649808    |
| camper    | -2.020951| .872054   | -2.32 | 0.020| -3.730146 -.3117567|
| _cons     | -2.695385| .8929071  | -3.02 | 0.003| -4.44545 -.9453189 |

| /lnalpha  | .5110429 | .1816816  | 2.81  | 0.005| .1549535 .8671323   |
| alpha     | 1.667029 | .3028685  |       |      | 1.167604 2.380076   |

The coefficients in the first equation of the coefficient table, labeled count, correspond to the negative binomial model for individuals who fished. For instance, among visitors who fished, using a live bait increases the expected number of caught fish by a factor of \( \exp(1.5575) \approx 4.7 \), holding other covariates constant.

The confidence interval for alpha indicates that the ZINB model is more appropriate than the ZIP model. To confirm this, you can run zinb and specify the zip option to obtain the ZIP likelihood-ratio test.

The inflate equation models whether the visitor does not fish. We can use margins to obtain a better understanding of how the inflate equation affects the occurrence of the excess zero counts. We specify margins's options dydx(child camper) and predict(pr). pr is predict's option
for estimating the probability of a degenerate zero or, in our example, the probability of not fishing; see the `margins` section in [R] zinb postestimation.

```
. margins, dydx(child camper) predict(pr)
```

```
Average marginal effects Number of obs = 250
Model VCE : OIM
Expression : Pr(count=0), predict(pr)
dy/dx w.r.t. : child camper
```

|          | dy/dx | Std. Err. | z     | P>|z|    | [95% Conf. Interval] |
|----------|-------|-----------|-------|--------|----------------------|
| child    | 0.257531 | 0.029941  | 8.60  | 0.000  | 0.1988477 - 0.3162144 |
| camper   | -0.1633578 | 0.0503938 | -3.24 | 0.001  | -0.2621277 - 0.0645878 |

The `margins` output tells us that a visitor is less likely to be visiting the park to fish if accompanied by children and more likely to fish if camping.

You also may want to evaluate whether a standard negative binomial model is adequate to fit the data. This can be done using information criteria; see example 2 in [R] zip.

### Stored results

`zinb` stores the following in `e()`:

**Scalars**

- `e(N)` number of observations
- `e(N_zero)` number of zero observations
- `e(k)` number of parameters
- `e(k_eq)` number of equations in `e(b)`
- `e(k_eq_model)` number of equations in overall model test
- `e(k_aux)` number of auxiliary parameters
- `e(k_dv)` number of dependent variables
- `e(df_m)` model degrees of freedom
- `e(ll)` log likelihood
- `e(ll_0)` log likelihood, constant-only model
- `e(df_c)` degrees of freedom for comparison test
- `e(N_clust)` number of clusters
- `e(chi2)` $\chi^2$
- `e(p)` p-value for model test
- `e(chi2_cp)` $\chi^2$ for test of $\alpha = 0$
- `e(rank)` rank of `e(V)`
- `e(ic)` number of iterations
- `e(rc)` return code
- `e(converged)` 1 if converged, 0 otherwise

**Macros**

- `e(cmd)` `zinb`
- `e(cmdline)` command as typed
- `e(depvar)` name of dependent variable
- `e(inflate)` logit or probit
- `e(utype)` weight type
- `e(wexp)` weight expression
- `e(title)` title in estimation output
- `e(clustvar)` name of cluster variable
- `e(offset1)` offset
- `e(offset2)` offset for `inflate()`
- `e(chi2type)` Wald or LR; type of model $\chi^2$ test
The **zinb** command maximizes a likelihood function that is a mixture of the logistic (or probit) and negative binomial distributions. The logistic distribution models the unobserved process that creates the excess zeros, and the negative binomial distribution models the counts. Define

\[
\begin{align*}
\xi_j^\beta &= x_j \beta + \text{offset}_j^\beta \\
\xi_j^\gamma &= z_j \gamma + \text{offset}_j^\gamma \\
\mu_j &= \exp(\xi_j^\beta) \\
p_j &= 1/(1 + \alpha \mu_j) \\
m &= 1/\alpha
\end{align*}
\]

Here, the vector \(x_j\) contains the covariates specified in *indepvars* for the \(j\)th observation, and \(z_j\) contains the covariates specified in the *inflate()* option. Similarly, estimates for \(\beta\) are found in the first equation of the **zinb** coefficient table (labeled after *depvar*), and the estimates for \(\gamma\) are found in the second equation of the coefficient table (labeled *inflate*). The parameter \(\alpha\) is the negative binomial overdispersion parameter, and its estimate is the ancillary parameter labeled *alpha* in the coefficient table. Parameters \(p_j, m, \) and \(\mu_j\) are parameters of a negative binomial distribution; see **Methods and formulas** in [R] *nbreg* for details.

The log likelihood maximized by **zinb** is

\[
\ln L = \sum_{j \in S} w_j \ln \left\{ F_j + (1 - F_j)p_j^m \right\} + \\
\sum_{j \not\in S} w_j \left\{ \ln(1 - F_j) + \ln\Gamma(m + y_j) - \ln\Gamma(y_j + 1) \\
- \ln\Gamma(m) + m \ln p_j + y_j \ln(1 - p_j) \right\}
\]
where \( w_j \) are the weights, \( S \) is the set of observations for which the observed outcome \( y_j = 0 \), and \( F_j \) is the logistic distribution function

\[
F_j = F(\xi_j^j) = \exp(\xi_j^j)/\{1 + \exp(\xi_j^j)\}
\]

or, if the \texttt{probit} option is specified, the standard normal distribution function

\[
F_j = F(\xi_j^j) = \Phi(\xi_j^j)
\]

From Long (1997), the variance of the mixture distribution is

\[
\text{Var}(y_j|x_i, z_i) = \mu_j(1 - F_j)\{1 + \mu_j(F_j + \alpha)\}
\]

When \( F_j \) is zero, we have the variance of the negative binomial distribution; when \( F_j > 0 \), the variance can exceed that of the negative binomial distribution.

This command supports the Huber/White/sandwich estimator of the variance and its clustered version using \texttt{vce(robust)} and \texttt{vce(cluster clustvar)}, respectively. See \texttt{[P] _robust}, particularly \textit{Maximum likelihood estimators} and \textit{Methods and formulas}.

\texttt{zinb} also supports estimation with survey data. For details on VCEs with survey data, see \texttt{[SVY] Variance estimation}.

### References


### Also see

- \texttt{zinb postestimation} — Postestimation tools for \texttt{zinb}
- \texttt{zip} — Zero-inflated Poisson regression
- \texttt{nbreg} — Negative binomial regression
- \texttt{poisson} — Poisson regression
- \texttt{tnbreg} — Truncated negative binomial regression
- \texttt{tpoisson} — Truncated Poisson regression
[BAYES] bayes: zinb — Bayesian zero-inflated negative binomial regression

[SVY] svy estimation — Estimation commands for survey data

[XT] xtnbreg — Fixed-effects, random-effects, & population-averaged negative binomial models

[U] 20 Estimation and postestimation commands