**poisson** — Poisson regression



## Description

`poisson` fits a Poisson regression of *depvar* on *indepvars*, where *depvar* is a nonnegative count variable.

If you have panel data, see [XT] **xtpoisson**.

## Quick start

Poisson regression of `y` on `x`

```
poisson y x
```

Add categorical variable `a`

```
poisson y x i.a
```

Add exposure variable `v`

```
poisson y x i.a, exposure(v)
```

With robust standard errors

```
poisson y x i.a, vce(robust)
```

Report results as incidence-rate ratios

```
poisson y x i.a, irr
```

Replace data in memory with the results of running a Poisson regression model on each level of `catvar`

```
statsby, by(catvar) clear: poisson y x
```

## Menu

Statistics > Count outcomes > Poisson regression

# Syntax

poisson *depvar* [*indepvars*] [*if*] [*in*] [*weight*] [, *options*]

| *options* | Description |
|---|---|
| **Model** | |
| noconstant | suppress constant term |
| exposure(*varname*$_e$) | include ln(*varname*$_e$) in model with coefficient constrained to 1 |
| offset(*varname*$_o$) | include *varname*$_o$ in model with coefficient constrained to 1 |
| constraints(*constraints*) | apply specified linear constraints |
| **SE/Robust** | |
| vce(*vcetype*) | *vcetype* may be oim, robust, cluster *clustvar*, opg, bootstrap, or jackknife |
| **Reporting** | |
| level(#) | set confidence level; default is level(95) |
| irr | report incidence-rate ratios |
| nocnsreport | do not display constraints |
| *display_options* | control columns and column formats, row spacing, line width, display of omitted variables and base and empty cells, and factor-variable labeling |
| **Maximization** | |
| *maximize_options* | control the maximization process; seldom used |
| collinear | keep collinear variables |
| coeflegend | display legend instead of statistics |

*indepvars* may contain factor variables; see **[U] 11.4.3 Factor variables**.

*depvar*, *indepvars*, *varname*$_e$, and *varname*$_o$ may contain time-series operators; see **[U] 11.4.4 Time-series varlists**.

bayes, bayesboot, bootstrap, by, fmm, fp, jackknife, mfp, mi estimate, nestreg, rolling, statsby, stepwise, and svy are allowed; see **[U] 11.1.10 Prefix commands**. For more details, see [BAYES] **bayes: poisson** and [FMM] **fmm: poisson**.

vce(bootstrap) and vce(jackknife) are not allowed with the mi estimate prefix; see [MI] **mi estimate**.

Weights are not allowed with the bootstrap prefix; see [R] **bootstrap**.

vce() and weights are not allowed with the svy prefix; see [SVY] **svy**.

fweights, iweights, and pweights are allowed; see **[U] 11.1.6 weight**.

collinear and coeflegend do not appear in the dialog box.

See **[U] 20 Estimation and postestimation commands** for more capabilities of estimation commands.

# Options

**Model**

noconstant, exposure(*varname*$_e$), offset(*varname*$_o$), constraints(*constraints*); see [R] **Estimation options**.

**SE/Robust**

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

Reporting

level(#); see [R] **Estimation options**.

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. irr may be specified at estimation or when replaying previously estimated results.

nocnsreport; see [R] **Estimation options**.

*display_options*: noci, nopvalues, noomitted, vsquish, noemptycells, baselevels, allbaselevels, nofvlabel, fvwrap(#), fvwrapon(*style*), cformat(%*fmt*), pformat(%*fmt*), sformat(%*fmt*), and nolstretch; see [R] **Estimation options**.

Maximization

*maximize_options*: difficult, technique(*algorithm_spec*), iterate(#), [no]log, trace, gradient, showstep, hessian, showtolerance, tolerance(#), ltolerance(#), nrtolerance(#), nonrtolerance, and from(*init_specs*); see [R] **Maximize**. These options are seldom used.

Setting the optimization type to technique(bhhh) resets the default *vcetype* to vce(opg).

The following options are available with poisson but are not shown in the dialog box:

collinear, coeflegend; see [R] **Estimation options**.

## Remarks and examples

The basic idea of Poisson regression was outlined by Coleman (1964, 378–379). See Cameron and Trivedi (2013; 2022, chap. 20) and Johnson, Kemp, and Kotz (2005, chap. 4) for information about the Poisson distribution. See Cameron and Trivedi (2013), Long (1997, chap. 8), Long and Freese (2014, chap. 9), McNeil (1996, chap. 6), and Selvin (2011, chap. 6) for an introduction to Poisson regression. Also see Selvin (2004, chap. 5) for a discussion of the analysis of spatial distributions, which includes a discussion of the Poisson distribution. An early example of Poisson regression was Cochran (1940).

Poisson regression fits models of the number of occurrences (counts) of an event. The Poisson distribution has been applied to diverse events, such as the number of soldiers kicked to death by horses in the Prussian army (von Bortkiewicz 1898); the pattern of hits by buzz bombs launched against London during World War II (Clarke 1946); telephone connections to a wrong number (Thorndike 1926); and disease incidence, typically with respect to time, but occasionally with respect to space. The basic assumptions are as follows:

1. There is a quantity called the *incidence rate* that is the rate at which events occur. Examples are 5 per second, 20 per 1,000 person-years, 17 per square meter, and 38 per cubic centimeter.
2. The incidence rate can be multiplied by *exposure* to obtain the expected number of observed events. For example, a rate of 5 per second multiplied by 30 seconds means that 150 events are expected; a rate of 20 per 1,000 person-years multiplied by 2,000 person-years means that 40 events are expected; and so on.
3. Over very small exposures $\epsilon$, the probability of finding more than one event is small compared with $\epsilon$.
4. Nonoverlapping exposures are mutually independent.

With these assumptions, to find the probability of $k$ events in an exposure of size $E$, you divide $E$ into $n$ subintervals $E_1$, $E_2$, …, $E_n$, and approximate the answer as the binomial probability of observing $k$ successes in $n$ trials. If you let $n \to \infty$, you obtain the Poisson distribution.

In the Poisson regression model, the incidence rate for the $j$th observation is assumed to be given by

$$r_j = e^{\beta_0+\beta_1 x_{1,j}+\cdots+\beta_k x_{k,j}}$$

If $E_j$ is the exposure, the expected number of events, $C_j$, will be

$$\begin{aligned} C_j &= E_j e^{\beta_0+\beta_1 x_{1,j}+\cdots+\beta_k x_{k,j}} \\ &= e^{\ln(E_j)+\beta_0+\beta_1 x_{1,j}+\cdots+\beta_k x_{k,j}} \end{aligned}$$

This model is fit by `poisson`. Without the `exposure()` or `offset()` options, $E_j$ is assumed to be 1 (equivalent to assuming that exposure is unknown), and controlling for exposure, if necessary, is your responsibility.

Comparing rates is most easily done by calculating *incidence-rate ratios* (IRRs). For instance, what is the relative incidence rate of chromosome interchanges in cells as the intensity of radiation increases; the relative incidence rate of telephone connections to a wrong number as load increases; or the relative incidence rate of deaths due to cancer for females relative to males? That is, you want to hold all the $x$'s in the model constant except one, say, the $i$th. The IRR for a one-unit change in $x_i$ is

$$\frac{e^{\ln(E)+\beta_1 x_1+\cdots+\beta_i(x_i+1)+\cdots+\beta_k x_k}}{e^{\ln(E)+\beta_1 x_1+\cdots+\beta_i x_i+\cdots+\beta_k x_k}} = e^{\beta_i}$$

More generally, the IRR for a $\Delta x_i$ change in $x_i$ is $e^{\beta_i \Delta x_i}$. The `lincom` command can be used after `poisson` to display incidence-rate ratios for any group relative to another; see [R] **lincom**.

## ▷ Example 1

Chatterjee and Hadi (2012, 174) give the number of injury incidents and the proportion of flights for each airline out of the total number of flights from New York for nine major US airlines in one year:

```
. use https://www.stata-press.com/data/r19/airline
. list
```

| | airline | injuries | n | XYZowned |
|---|---|---|---|---|
| 1. | 1 | 11 | 0.0950 | 1 |
| 2. | 2 | 7 | 0.1920 | 0 |
| 3. | 3 | 7 | 0.0750 | 0 |
| 4. | 4 | 19 | 0.2078 | 0 |
| 5. | 5 | 9 | 0.1382 | 0 |
| 6. | 6 | 4 | 0.0540 | 1 |
| 7. | 7 | 3 | 0.1292 | 0 |
| 8. | 8 | 1 | 0.0503 | 0 |
| 9. | 9 | 3 | 0.0629 | 1 |

To their data, we have added a fictional variable, XYZowned. We will imagine that an accusation is made that the airlines owned by XYZ Company have a higher injury rate.

```
. poisson injuries XYZowned, exposure(n) irr
Iteration 0:  Log likelihood = -23.027197
Iteration 1:  Log likelihood = -23.027177
Iteration 2:  Log likelihood = -23.027177
Poisson regression                                      Number of obs =      9
                                                        LR chi2(1)    =   1.77
                                                        Prob > chi2   = 0.1836
Log likelihood = -23.027177                             Pseudo R2     = 0.0370
------------------------------------------------------------------------------
    injuries |        IRR   Std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
    XYZowned |   1.463467    .406872     1.37   0.171     .8486578    2.523675
       _cons |   58.04416   8.558145    27.54   0.000     43.47662    77.49281
      ln(n) |          1  (exposure)
------------------------------------------------------------------------------
Note: _cons estimates baseline incidence rate.
```

We specified `irr` to see the IRRs rather than the underlying coefficients. We estimate that XYZ Airlines' injury rate is 1.46 times larger than that for other airlines, but the 95% confidence interval is 0.85 to 2.52; we cannot even reject the hypothesis that XYZ Airlines has a lower injury rate.

◁

## ❑ Technical note

In example 1, we assumed that each airline's exposure was proportional to its fraction of flights out of New York. What if "large" airlines, however, also used larger planes, and so had even more passengers than would be expected, given this measure of exposure? A better measure would be each airline's fraction of passengers on flights out of New York, a number that we do not have. Even so, we suppose that n represents this number to some extent, so a better estimate of the effect might be

```
. generate lnN=ln(n)
. poisson injuries XYZowned lnN
Iteration 0:  Log likelihood = -22.333875
Iteration 1:  Log likelihood = -22.332276
Iteration 2:  Log likelihood = -22.332276
Poisson regression                                      Number of obs =      9
                                                        LR chi2(2)    =  19.15
                                                        Prob > chi2   = 0.0001
Log likelihood = -22.332276                             Pseudo R2     = 0.3001
------------------------------------------------------------------------------
    injuries |  Coefficient  Std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
    XYZowned |   .6840667   .3895877     1.76   0.079    -.0795111    1.447645
         lnN |   1.424169   .3725155     3.82   0.000     .6940517    2.154285
       _cons |   4.863891   .7090501     6.86   0.000     3.474178    6.253603
------------------------------------------------------------------------------
```

Here rather than specifying the `exposure()` option, we explicitly included the variable that would normalize for exposure in the model. We did not specify the `irr` option, so we see coefficients rather than IRRs. We started with the model

$$\text{rate} = e^{\beta_0+\beta_1 \text{XYZowned}}$$

The observed counts are therefore

$$\text{count} = ne^{\beta_0+\beta_1\text{XYZowned}} = e^{\ln(n)+\beta_0+\beta_1\text{XYZowned}}$$

which amounts to constraining the coefficient on ln(n) to 1. This is what was estimated when we specified the `exposure(n)` option. In the above model, we included the normalizing exposure ourselves and, rather than constraining the coefficient to be 1, estimated the coefficient.

The estimated coefficient is 1.42, a respectable distance away from 1, and is consistent with our speculation that larger airlines also use larger airplanes. With this small amount of data, however, we also have a wide confidence interval that includes 1.

Our estimated *coefficient* on `XYZowned` is now 0.684, and the implied IRR is $e^{0.684} \approx 1.98$ (which we could also see by typing `poisson, irr`). The 95% confidence interval for the coefficient still includes 0 (the interval for the IRR includes 1), so although the point estimate is now larger, we still cannot be certain of our results.

Our expert opinion would be that, although there is not enough evidence to support the charge, there is enough evidence to justify collecting more data.

❑

## ▷ Example 2

In a famous age-specific study of coronary disease deaths among male British doctors, Doll and Hill (1966) reported the following data (reprinted in Lash et al. [2021, 417]):

| | Smokers | | Nonsmokers | |
|---|---|---|---|---|
| Age | Deaths | Person-years | Deaths | Person-years |
| 35–44 | 32 | 52,407 | 2 | 18,790 |
| 45–54 | 104 | 43,248 | 12 | 10,673 |
| 55–64 | 206 | 28,612 | 28 | 5,710 |
| 65–74 | 186 | 12,663 | 28 | 2,585 |
| 75–84 | 102 | 5,317 | 31 | 1,462 |

The first step is to enter these data into Stata, which we have done:

```
. use https://www.stata-press.com/data/r19/dollhill3, clear
(Doll and Hill (1966))
. list
```

| | agecat | smokes | deaths | pyears |
|---|---|---|---|---|
| 1. | 35-44 | 1 | 32 | 52,407 |
| 2. | 45-54 | 1 | 104 | 43,248 |
| 3. | 55-64 | 1 | 206 | 28,612 |
| 4. | 65-74 | 1 | 186 | 12,663 |
| 5. | 75-84 | 1 | 102 | 5,317 |
| 6. | 35-44 | 0 | 2 | 18,790 |
| 7. | 45-54 | 0 | 12 | 10,673 |
| 8. | 55-64 | 0 | 28 | 5,710 |
| 9. | 65-74 | 0 | 28 | 2,585 |
| 10. | 75-84 | 0 | 31 | 1,462 |

The most "natural" analysis of these data would begin by introducing indicator variables for each age category and one indicator for smoking:

```
. poisson deaths smokes i.agecat, exposure(pyears) irr
Iteration 0:  Log likelihood = -33.823284
Iteration 1:  Log likelihood = -33.600471
Iteration 2:  Log likelihood = -33.600153
Iteration 3:  Log likelihood = -33.600153
Poisson regression                                      Number of obs =     10
                                                        LR chi2(5)    = 922.93
                                                        Prob > chi2   = 0.0000
Log likelihood = -33.600153                             Pseudo R2     = 0.9321
------------------------------------------------------------------------------
      deaths |        IRR   Std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
      smokes |   1.425519   .1530638     3.30   0.001     1.154984    1.759421
             |
      agecat |
       45-54 |   4.410584   .8605197     7.61   0.000     3.009011    6.464997
       55-64 |    13.8392   2.542638    14.30   0.000     9.654328    19.83809
       65-74 |   28.51678   5.269878    18.13   0.000     19.85177    40.96395
       75-84 |   40.45121   7.775511    19.25   0.000     27.75326    58.95885
             |
       _cons |   .0003636   .0000697   -41.30   0.000     .0002497    .0005296
 ln(pyears)  |          1  (exposure)
------------------------------------------------------------------------------
Note: _cons estimates baseline incidence rate.
```

In the above, we specified `irr` to obtain IRRs. We estimate that smokers have 1.43 times the mortality rate of nonsmokers. See, however, example 1 in [R] **poisson postestimation**.

## Stored results

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

Scalars

| | |
|---|---|
| `e(N)` | number of 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_dv)` | number of dependent variables |
| `e(df_m)` | model degrees of freedom |
| `e(r2_p)` | pseudo-$R^2$ |
| `e(ll)` | log likelihood |
| `e(ll_0)` | log likelihood, constant-only model |
| `e(N_clust)` | number of clusters |
| `e(chi2)` | $\chi^2$ |
| `e(p)` | $p$-value for model test |
| `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)` | `poisson` |
| `e(cmdline)` | command as typed |
| `e(depvar)` | name of dependent variable |
| `e(wtype)` | weight type |

| | |
|---|---|
| e(wexp) | weight expression |
| e(title) | title in estimation output |
| e(clustvar) | name of cluster variable |
| e(offset) | linear offset variable |
| e(chi2type) | Wald or LR; type of model $\chi^2$ test |
| e(vce) | *vcetype* specified in vce() |
| e(vcetype) | title used to label Std. err. |
| e(opt) | type of optimization |
| e(which) | max or min; whether optimizer is to perform maximization or minimization |
| e(ml_method) | type of ml method |
| e(user) | name of likelihood-evaluator program |
| e(technique) | maximization technique |
| e(properties) | b V |
| e(estat_cmd) | program used to implement estat |
| e(predict) | program used to implement predict |
| e(asbalanced) | factor variables fvset as asbalanced |
| e(asobserved) | factor variables fvset as asobserved |

Matrices

| | |
|---|---|
| e(b) | coefficient vector |
| e(Cns) | constraints matrix |
| e(ilog) | iteration log (up to 20 iterations) |
| e(gradient) | gradient vector |
| e(V) | variance–covariance matrix of the estimators |
| e(V_modelbased) | model-based variance |

Functions

| | |
|---|---|
| e(sample) | marks estimation sample |

In addition to the above, the following is stored in r():

Matrices

| | |
|---|---|
| r(table) | matrix containing the coefficients with their standard errors, test statistics, $p$-values, and confidence intervals |

Note that results stored in r() are updated when the command is replayed and will be replaced when any r-class command is run after the estimation command.

## Methods and formulas

The log likelihood (with weights $w_j$ and offsets) is given by

$$\Pr(Y = y) = \frac{e^{-\lambda}\lambda^{y}}{y!}$$

$$\xi_j = \mathbf{x}_j\boldsymbol{\beta} + \text{offset}_j$$

$$f(y_j) = \frac{e^{-\exp(\xi_j)}e^{\xi_j y_j}}{y_j!}$$

$$\ln L = \sum_{j=1}^{n} w_j \left\{-e^{\xi_j} + \xi_j y_j - \ln(y_j!)\right\}$$

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

poisson also supports estimation with survey data. For details on VCEs with survey data, see [SVY] **Variance estimation**.

Siméon-Denis Poisson (1781–1840) was a French mathematician and physicist who contributed to several fields: his name is perpetuated in Poisson brackets, Poisson's constant, Poisson's differential equation, Poisson's integral, and Poisson's ratio. Among many other results, he produced a version of the law of large numbers. His rather misleadingly titled *Recherches sur la probabilité des jugements* embraces a complete treatise on probability, as the subtitle indicates, including what is now known as the Poisson distribution. That, however, was discovered earlier by the Huguenot–British mathematician Abraham de Moivre (1667–1754).

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## Also see

[R] **poisson postestimation** — Postestimation tools for poisson

[R] **glm** — Generalized linear models

[R] **heckpoisson** — Poisson regression with sample selection

[R] **nbreg** — Negative binomial regression

[R] **npregress kernel** — Nonparametric kernel regression

[R] **npregress series** — Nonparametric series regression

[R] **tpoisson** — Truncated Poisson regression

[R] **zip** — Zero-inflated Poisson regression

[BAYES] **bayes: poisson** — Bayesian Poisson regression

[FMM] **fmm: poisson** — Finite mixtures of Poisson regression models

[LASSO] **Lasso intro** — Introduction to lasso

[ME] **mepoisson** — Multilevel mixed-effects Poisson regression

[MI] **Estimation** — Estimation commands for use with mi estimate

[SVY] **svy estimation** — Estimation commands for survey data

[XT] **xtpoisson** — Fixed-effects, random-effects, and population-averaged Poisson models

**[U] 20 Estimation and postestimation commands**