The Chi-Square Diagnostic Test
for Count Data Models

M. Manjón-Antolín and O. Martínez-Ibañez

QURE-CREIP Department of Economics, Rovira i Virgili University.

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The Pearson chi-squared goodness-of-fit test is a diagnostic tests implemented in Stata as a post estimation command, `estat gof`, to be used after `logit`, `logistic`, `probit` and `poisson` commands.
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Moreover, the `group()` option yields the related Hosmer–Lemeshow test.
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However, the Pearson and Hosmer–Lemeshow tests assume that the estimated coefficients are known.
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However, the Pearson and Hosmer–Lemeshow tests assume that the estimated coefficients are known.

To control for the potential estimation error, Cameron and Trivedi (2009) suggest using the Chi-Square Diagnostic Test developed by Andrews (1988a, 1988b).
This Chi-Square Diagnostic Test compares the sample relative frequencies of the dependent variable with the predicted frequencies from the model using a quadratic form and an estimate of the asymptotic variance of the corresponding population moment condition.
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However, to date this $m$-test is not available in Stata.
This paper discusses the implementation of the Chi-square Diagnostic Test of Andrews (1988a, 1988b) in count data models as a Stata post-estimation command.
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In particular, \texttt{chisqdt} can be used right after \texttt{poisson}, \texttt{nbreg}, \texttt{zip} and \texttt{zinb} commands.
This paper discusses the implementation of the Chi-square Diagnostic Test of Andrews (1988a, 1988b) in count data models as a Stata post-estimation command.

In particular, `chisqdt` can be used right after `poisson`, `nbreg`, `zip` and `zinb` commands.

The new command, `chisqdt`, reports the test statistic and its p-value.

Also, one may obtain a table with the actual, predicted and absolute differences between actual and predicted probabilities.
Introduction

The Chi-square Diagnostic Test: Theory

The chisqdt command

Examples

References

Let us consider a model given by $f(y|w,\theta)$, the conditional density of the variable of interest ($y$) given a set of covariates ($w$) and a vector of parameters ($\theta$). In particular, we are interested in the conditional density of the Poisson, Negative Binomial, Zero-Inflated Poisson and Zero-Inflated negative binomial models. Thus, $w = x$ in the Poisson and Negative Binomial models and $w = \{x, z\}$ in the inflated versions.

Also, let $J$ be the number of (mutually exclusive) cells in which the range of the dependent variable $y$ is partitioned ($i = 1, \cdots, N$).

Lastly, let $d_{ij}(y_i) = 1$ if observation $i$ belongs to cell $j$ and zero otherwise.

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Also, let $J$ be the number of (mutually exclusive) cells in which the range of the dependent variable $y_i$ is partitioned ($i = 1, \cdots, N$).

Lastly, let $d_{ij}(y_i) = 1(y_i \in j)$ be an indicator variable that takes value one if observation $i$ belongs to cell $j$ and zero otherwise.
If the model is correctly specified, then

$$E[di(y_i) - p_{ij}(w_i, \theta)] = 0,$$

where $p_{ij}(w_i, \theta)$ is the probability that observation $i$ falls in cell $j$ according to $f(y|w, \theta)$. 
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In particular, stacking all $J$ moments in vector notation we obtain

$$E[d_i(y_i) - p_i(w_i, \theta)] = 0.$$
Given a sample analog:

\[ \hat{m}_N(\hat{\theta}) = \frac{1}{N} \sum_{i=1}^{N} [d_i(y_i) - p_i(w_i, \hat{\theta})], \]
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the Chi-Square Diagnostic Test of Andrews (1988a, 1988b) is

\[ chisqdt = N\hat{m}_N(\hat{\theta})\hat{V}^{-1}\hat{m}_N(\hat{\theta}). \]

where \( V \) is a variance-covariance matrix given by \( \sqrt{N}\hat{m}_N(\hat{\theta}) \rightarrow \mathcal{N}(0, V) \).
Under the null hypothesis that the moment condition holds, the \texttt{chisqdt} test is asymptotically $\chi^2$—distributed with $\text{rank}[V]$ degrees of freedom.
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Moreover, the computation of this variance-covariance matrix is often complicated.
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This is just $N$ times the (uncentered) $R^2$ of the following auxiliary regression:

$$1 = \hat{m}_i \delta + \hat{s}_i \gamma + u_i,$$

where $1$ is a column vector of $N$ ones, $\hat{m}_i$ includes $d_{ij}(y_i) - p_{ij}(w_i, \hat{\theta}^{ML})$ for $j = 1, \ldots, J - 1$ and $\hat{s}_i = \frac{\partial \log f(y_i|w_i, \theta)}{\partial \theta} \bigg|_{\theta=\hat{\theta}^{ML}}$ is the matrix of contributions to the score evaluated at the maximum likelihood estimate of $\theta$. 

The Chi-Square Diagnostic Test for Count Data Models
In particular, it is easy to see that

\[ chisqdt = N \times R^2 = 1' H (H' H)^{-1} H' 1, \]

where \( H_i = [\hat{m}_i, \hat{s}_i] \) is the \( i \)-th row of matrix \( H \).

This asymptotically equivalent version of (7) is the one used in the computation of \texttt{chisqdt}.

Notice that all is needed to compute the test are the predicted probabilities \((p_{ij})\) and the scores \((\hat{s}_i)\). The paper provides detailed formulae; see also Greene (1994), Cameron and Trivedi (1998) and Cameron and Trivedi (2005).
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Under the null hypothesis of correct specification of the model, this statistic asymptotically follows a \( \chi^2 \) distribution with \( J - 1 \) degrees of freedom.
The syntax of the command is the following:

```
chisqdt ,
cells(#) [prcount] [table]
```

where `cells` is the number of (mutually exclusive) cells in which one partitions the range of the dependent variable to compute the test. In principle, any partition of the dependent variable can be used. For example, if one uses three cells the following partitions can be used:

- `{0, 1, 2, 3}`
- `{4, 5}`
- `{6, 7, ... , ∞}`
- `{0, 1}`
- `{2, 3, 4, 5}`
- `{6}`
- `{7, 8, ... , ∞}`
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- `{6}`
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- etc.
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In principle, any partition of the dependent variable can be used.

For example, if one uses three cells the following partitions can be used: \{0, 1, 2, 3\}, \{4, 5\} and \{6, 7, \ldots, \infty\}; \{0, 1\}, \{2, 3, 4, 5\} and \{6, 7, \ldots, \infty\}; \{0, 1, 2, 3, 4, 5\}, \{6\} and \{7, 8, \ldots, \infty\}; etc.
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That is, \texttt{chisqdt} uses partitions like \{0\} and \{1, 2, 3, \ldots, \infty\}; \{0\}, \{1\} and \{2, 3, \ldots, \infty\}; \{0\}, \{1\}, \{2\} and \{3, 4, \ldots, \infty\}; and so on.
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In general, for cells\( (J) \), the partition **chisqdt** uses is \{0\}, \{1\}, \{2\}, \ldots, \{J – 2\} and \{J – 1, \ldots, \infty\}. 
## Syntax

<table>
<thead>
<tr>
<th>Options</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
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</tr>
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<td><code>table</code></td>
<td>A table with the actual, predicted and absolute differences between actual and predicted frequencies is reported.</td>
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### Options

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By default the program calculates these predicted probabilities (or predicted frequencies) using the definition of the conditional density of the dependent variable (direct).
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However, one may alternatively compute these probabilities using the program `prcounts` of Long and Freese (2001, Stata *Journal* 1).
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In general, results barely change when using one or the other.
Differences do arise, however, when the number of counts is high, particularly if the (zero-inflated) negative binomial model is used.
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In that case, one receives an error message informing that “Missing values encountered when “prcount“ option is used (try “direct” option)”.\[\alpha\]
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One also receives an error message when the statistic may not be computed for the (zero-inflated) negative binomial model because the $\alpha$ parameter is too small: “Problem with alpha prevents estimation of predicted probabilities (alpha too small)”.
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Ultimately, both error messages arise because of the large numbers that the gamma function generates.
The option `table` produces a table with the actual, predicted and absolute differences between actual and predicted frequencies.
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This can be useful in assessing the adequacy of the partition of the dependent variable we are using. As the examples will show, this may e.g. help detecting cells with too few observations.
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This can be useful in assessing the adequacy of the partition of the dependent variable we are using. As the examples will show, this may e.g. help detecting cells with too few observations.

Also, the table may provide insights about the source of misspecification. In the `poisson` model, for example, big absolute differences in the zero value may indicate overdispersion.
We illustrate the use of the new command and the interpretation of its output with three examples. The first example merely replicates results from chapters 5–6 of Cameron and Trivedi (1998). This is the one we report here. The second and third examples replicate and extend results reported in chapter 17 of Cameron and Trivedi (2009). In all the cases we report the output resulting from both the estimation command (``poisson'', ``nbreg'', ``zip'' or ``zinb'') and the new command (``chisqdt''). In particular, in the first example we also report the table with the actual, predicted and absolute differences between actual and predicted frequencies (option `table`).
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In particular, in the first example we also report the table with the actual, predicted and absolute differences between actual and predicted frequencies (option table).
Exemple 1.

Cameron and Trivedi (1998) analyse the determinants of takeover bids using a sample of 126 US firms that were taken over between 1978 and 1985.

The dependent variable is the number of bids received by the firm after the initial tender offer (numbids), while covariates include defensive actions taken by the management of the firm (leglrest, realrest, finestrest and whtknght), firm-specific characteristics (bidprem, insthold, size and sizesq), and intervention by federal regulators (regulatn).

The relation between the dependent and explanatory variables is estimated using the Poisson regression model.
Results can be obtained by typing

```
.infile docno weeks numbids takeover bidprem insthold size
leglrest realrest finrest regulatn whtkncht sizesq constant using
http://cameron.econ.ucdavis.edu/racd/racd5.asc, clear
(126 observations read)

.poisson numbids leglrest realrest finrest whtkncht bidprem insthold size
sizesq regulatn, nolog
```
Results can be obtained by typing

```stata
.infile docno weeks numbids takeover bidprem insthold size leglrest realrest finrest regulatn whtknght sizesq constant using
http://cameron.econ.ucdavis.edu/racd/racd5.asc, clear
(126 observations read)

.poiisson numbids leglrest realrest finrest whtknght bidprem insthold size sizesq regulatn, nolog
```

And the resulting output, including the Chi-square Diagnostic Test with $J = 6$, is
### Poisson regression

| Variable    | Coef.    | Std. Err. | z    | P>|z|   | [95% Conf. Interval] |
|-------------|----------|-----------|------|-------|---------------------|
| leglrest    | 0.2601464| 0.1509594 | 1.72 | 0.085 | -0.0357286 to 0.5560213 |
| realrest    | -0.1956597| 0.1926309 | -1.02| 0.310 | -0.5732093 to 0.1818899 |
| finrest     | 0.0740301| 0.2165219 | 0.34 | 0.732 | -0.3503452 to 0.4984053 |
| whtknght    | 0.4813822| 0.1588698 | 3.03 | 0.002 | 0.170003 to 0.7927613  |
| bidprem     | -0.6776958| 0.3767372 | -1.80| 0.072 | -1.416087 to 0.0606956 |
| instthold   | -0.3619912| 0.4243292 | -0.85| 0.394 | -1.193661 to 0.4696788 |
| size        | 0.1785026| 0.0600221 | 2.97 | 0.003 | 0.0608614 to 0.2961438 |
| sizesq      | -0.0075693| 0.0031217 | -2.42| 0.015 | -0.0136878 to 0.0014509 |
| regulatn    | -0.0294392| 0.1605682 | -0.18| 0.855 | -0.344147 to 0.2852686 |
| _cons       | 0.9860598| 0.5339201 | 1.85 | 0.065 | -0.0604044 to 2.032524 |

```
. chisqdt, cells(6)
Chi-squared Test for Poisson Model =  48.66  (Prob>chi2 = 0.00)
```
Also, we can obtain the table the actual, predicted and absolute differences between actual and predicted probabilities by typing

\[ \text{. chisqdt, cells(6) table} \]

Chi-squared Test for ZIP Model = 94.13 (Prob>chi2 = 0.00)

<table>
<thead>
<tr>
<th>Counts</th>
<th>Actual</th>
<th>Predicted</th>
<th>Abs. Dif.</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>.6328</td>
<td>.6285</td>
<td>.0042</td>
</tr>
<tr>
<td>1</td>
<td>.1032</td>
<td>.0373</td>
<td>.0659</td>
</tr>
<tr>
<td>2</td>
<td>.0577</td>
<td>.0471</td>
<td>.0106</td>
</tr>
<tr>
<td>3</td>
<td>.0516</td>
<td>.0489</td>
<td>.0027</td>
</tr>
<tr>
<td>4</td>
<td>.0258</td>
<td>.0455</td>
<td>.0197</td>
</tr>
<tr>
<td>5 or more</td>
<td>.129</td>
<td>.1927</td>
<td>.0637</td>
</tr>
</tbody>
</table>
Exemple 1 (Continuation).

The second application we consider is their analysis of the determinants of the number of recreational boating trips to Lake Somerville, Texas, in 1980 (trips).

Covariates include a subjective quality index of the facility (so), a dummy variable to indicate practice of water-skiing at the lake (ski), the household income of the head of the group (i), a dummy variable to indicate whether the user paid a fee (fc3), dollar expenditure when visiting Lake Conroe (c1), dollar expenditure when visiting Lake Somerville (educyr), and dollar expenditure when visiting Lake Houston (educyr).
In their analyses Cameron and Trivedi (1998) discuss at length different models (including finite mixtures and hurdle-types of the Poisson and the negative binomial models) and goodness-of-fit measures (the $G^2$ statistic, the pseudo-$R^2$, etc.). However, we limit the reported results to the `poisson`, `nbreg` and `zip` estimates and the Chi-Square Diagnostic Test, `chisqdt`. 
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In particular, results can be obtained by typing

```
.infile trips so ski i fc3 c1 c3 c4 using http://cameron.econ.ucdavis.edu/racd
> /racd6d2.asc, clear
(659 observations read)
.poisson trips so ski i fc3 c1 c3 c4, nolog
.chisqdt, cells(6)
.nbreg trips so ski i fc3 c1 c3 c4, nolog
.chisqdt, cells(6)
.zip trips so ski i fc3 c1 c3 c4, inflate(so i) nolog
.chisqdt, cells(6)
```
Poisson regression

Log likelihood = -1529.4313

Number of obs = 659
LR chi2(7) = 2543.90
Prob > chi2 = 0.0000
Pseudo R2 = 0.4540

| trips | Coef. | Std. Err. | z    | P>|z| | [95% Conf. Interval] |
|-------|------|-----------|------|-----|----------------------|
| so    | 0.4717259 | 0.0170905 | 27.60 | 0.000 | 0.4382291 - 0.5052227 |
| ski   | 0.4182137 | 0.0571905 | 7.31  | 0.000 | 0.3061224 - 0.5303051 |
| i     | -0.1113232 | 0.0195885 | -5.68 | 0.000 | -0.1497159 - 0.0729304 |
| fc3   | 0.8981652 | 0.0789854 | 11.37 | 0.000 | 0.7433567 - 1.052974 |
| c1    | -0.0034297 | 0.0031178 | -1.10 | 0.271 | -0.0095405 - 0.0026811 |
| c3    | -0.0425364 | 0.0016703 | -25.47 | 0.000 | -0.0458102 - 0.0392626 |
| c4    | 0.0361336 | 0.0027096 | 13.34 | 0.000 | 0.0308229 - 0.0414444 |
| _cons | 0.2649934 | 0.0937224 | 2.83  | 0.005 | 0.0813009 - 0.4486859 |

Chi-squared Test for Poisson Model = 252.57 (Prob>chi2 = 0.00)
Negative binomial regression

|          | Coef.  | Std. Err. |   z  | P>|z|  | [95% Conf. Interval] |
|----------|--------|-----------|------|------|---------------------|
| trips    |        |           |      |      |                     |
| so       | .721999| .0453323  | 15.93| 0.000| .6331493            | .8108487 |
| ski      | .6121388| .1504163 | 4.07 | 0.000| .3173282            | .9069493 |
| i        | -.0260589| .0452342 | -0.58| 0.565| -.1147163           | .0625986 |
| fc3      | .6691677| .3614399  | 1.85 | 0.064| -.0392415           | 1.377577 |
| c1       | .0480086| .0159516  | 3.01 | 0.003| .016744             | .0792732 |
| c3       | -.092691| .0082685  | -11.21| 0.000| -.1088969           | -.0764851 |
| c4       | .0388357| .0117139  | 3.32 | 0.001| .0158769            | .0617945 |
| _cons    | -1.121936| .2208284 | -5.08| 0.000| -1.554752           | -.6891205 |
| /lnalpha | .3157293| .1060209  |      |      | .1079321            | .5235264 |
| alpha    | 1.371259| .1453821  |      |      | 1.113972            | 1.68797   |

Likelihood-ratio test of alpha=0: chibar2(01) = 1407.75 Prob>=chibar2 = 0.000
Chi-squared Test for NegBin Model = 23.54 (Prob>chi2 = 0.00)
Zero-inflated Poisson regression

Number of obs = 659
Nonzero obs = 242
Zero obs = 417

Inflation model = logit
LR chi2(7) = 622.01
Log likelihood = -1180.795 Prob > chi2 = 0.0000

|        | Coef.  | Std. Err. | z     | P>|z|   | [95% Conf. Interval] |
|--------|--------|-----------|-------|-------|----------------------|
| trips  |        |           |       |       |                      |
| so     | 0.0338331 | 0.0239159 | 1.41  | 0.157 | -0.0130412 - 0.0807073 |
| ski    | 0.4716906 | 0.0581895 | 8.11  | 0.000 | 0.3576412 - 0.585744  |
| i      | -0.0997796 | 0.0207787 | -4.80 | 0.000 | -0.1405052 - 0.059054 |
| fc3    | 0.6104876 | 0.0794354 | 7.69  | 0.000 | 0.4547972 - 0.7661781 |
| c1     | 0.0023689 | 0.0038282 | 0.62  | 0.536 | -0.0051343 - 0.009872 |
| c3     | -0.0376003 | 0.002039  | -18.44 | 0.000 | -0.0415966 - 0.033604 |
| c4     | 0.0252337 | 0.0033666 | 7.50  | 0.000 | 0.0186353 - 0.0318321 |
| _cons | 2.099162  | 1.114393  | 18.84 | 0.000 | 1.880745 - 2.317579   |

(Inflated part omitted)
Chi-squared Test for ZIP Model = 94.13 (Prob>chi2 = 0.00)


Cameron, A.C. and Trivedi, P.K. (2005): *Microeconometrics*, CUP.


The Chi-Square Diagnostic Test for Count Data Models

M. Manjón-Antolín and O. Martínez-Ibañez

QURE-CREIP Department of Economics, Rovira i Virgili University.

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