

# How can I perform the likelihood ratio and Wald test in Stata?

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The likelihood ratio and Wald test are two commonly used statistical tests in Stata. These tests are used to assess the significance of predictor variables in a regression model. To perform the likelihood ratio test, the "lrtest" command is used, which compares the likelihood of a full model to a reduced model. The resulting p-value indicates whether the addition of the predictor variable significantly improves the model's fit. On the other hand, the Wald test is performed using the "test" command, which calculates a z-statistic and corresponding p-value for the individual predictor variable. This test evaluates the significance of each predictor variable separately. Both tests are important tools for determining the importance of predictor variables in a regression model and can be easily performed in Stata with the appropriate commands.

## How can I perform the likelihood ratio and Wald test in Stata? | Stata FAQ

**Purpose:** This page shows you how to conduct a likelihood ratio test and Wald test in Stata. For a more conceptual understanding, including an explanation of the score test, refer to the FAQ page [How are the likelihood ratio, Wald, and Lagrange multiplier \(score\) tests different and/or similar?](#)

The likelihood ratio (LR) test and Wald test are commonly used to evaluate the difference between nested models.

One model is considered nested in another if the first model can be generated by imposing restrictions on the parameters of the second. Most often, the restriction is that the parameter is equal to zero. In a

## regression model

restricting a parameters to zero is accomplished by removing the predictor variables from the model. For example, in the models below, the model with the predictor variables female, and read, is nested within

the model with the predictor variables female, read, math, and

science. The LR and Wald ask the same basic question, which is, does constraining these parameters to zero (i.e., leaving out these predictor variables) significantly reduce the fit

of the model? To perform a likelihood ratio test, one must estimate both of the

models one wishes to compare. The

advantage of the Wald test is that it approximates the LR test but

require that only one model be estimated. When computing power was much more limited, and many models took

a long time to run, this was a fairly major advantage.

Today, for most of the models

researchers are likely to want to compare, this is not an issue, and we generally

**recommend**

**running the likelihood ratio test in most situations. This is not to say that**

**one should never use the Wald test. For example, the Wald test is**

**commonly used to perform multiple degree of freedom tests on sets of dummy**

**variables used to model categorical variables in regression (for more**

**information see our webbook on Regression with Stata, specifically**

**Chapter 3 - Regression with Categorical Predictors).**

**As we mentioned above, the LR test requires that two models be run, one of which**

**has a set of parameters (variables), and a second model with all of the parameters**

**from the first, plus one or more other variables. The**

**Wald test examines a model with**

**more parameters and assess whether restricting those parameters (generally to zero, by**

**removing the associated variables from the model) seriously harms the fit of the model.**

**In general, both tests should come to the same**

**conclusion (because the Wald test, at least in theory, approximate the LR test). As an example, we will test for a statistically significant difference between two models, using both tests.**

**The dataset for this example includes demographic data, as well as standardized test scores for 200 high school students. We will compare two models. The dependent variable for both models is hiwrite (to be nested two models must share the same dependent variable), which is a dichotomous variable indicating that the student had a writing score that was above the mean. There are four possible predictor variables, female, a dummy variable which indicates that the student is female, and the continuous variables read, math, and science, which are the student's standardized test scores in reading, math, and science, respectively. We will test a model containing just the predictor**

**variables female and read, against a model that contains the predictor variables female and read, as well as, the additional predictor variables, math and science.**

**Example of a likelihood ratio test.**

**As discussed above, the LR test involves estimating two models and comparing them. Fixing one or more parameters to zero, by removing the variables associated with that parameter from the model, will almost always make the model fit less well, so a change in the log likelihood does not necessarily mean the model with more variables fits significantly better. The LR test compares the log likelihoods of the two models and tests whether this difference is statistically significant. If the difference is statistically significant, then the less restrictive model (the one with more variables) is said to fit the data significantly better than the more restrictive model. The LR test statistic is**

calculated in the following way:

$$LR = -2 \ln \left( \frac{L(m_1)}{L(m_2)} \right) = 2(\loglik(m_2) - \loglik(m_1))$$

Where  $L(m_*)$  denotes the likelihood of the respective model (either Model 1 or Model 2), and  $\loglik(m_*)$  the natural log of the model's final likelihood (i.e., the log likelihood). Where  $m_1$  is the more restrictive model, and  $m_2$  is the less restrictive model.

This statistic is distributed chi-squared with degrees of freedom equal to the difference in the number of degrees of freedom between the two models (i.e., the number of variables added to the model).

In order to perform the likelihood ratio test we will need to run both models and make note of their final log likelihoods. We will run the models using Stata and use commands to store the log likelihoods. We could also just copy the likelihoods down (i.e., by writing them down, or cutting and pasting), but using commands is a little

easier and is less likely to result in errors. The first line of syntax below reads in the dataset from our website. The second line of syntax runs a logistic regression model, predicting hiwrite based on students' gender (female), and reading scores (read). The third line of code stores the value of the log likelihood for the model, which is temporarily stored as the returned estimate e(ll) (for more information type help return in the Stata command window), in the scalar named m1.

use

[https://stats.idre.ucla.edu/stat/stata/faq/nested\\_tests](https://stats.idre.ucla.edu/stat/stata/faq/nested_tests),

clear

logit hiwrite female read

scalar m1 = e(ll)

Below is the output. In order to perform the likelihood ratio test we will need to keep track of the log likelihood (-102.44), the syntax for this example (above) does this

by storing the value in a scalar. Since it is not our primary concern here, we will skip the interpretation of the rest logistic regression model. Note that storing the returned estimate does not produce any output.

Iteration 0: log likelihood = -137.41698

Iteration 1: log likelihood = -104.79885

Iteration 2: log likelihood = -102.52269

Iteration 3: log likelihood = -102.44531

Iteration 4: log likelihood = -102.44518

Logistic regression Number of obs = 200

LR chi2(2) = 69.94

Prob > chi2 = 0.0000

Log likelihood = -102.44518 Pseudo R2 = 0.2545

-----  
 hiwrite | Coef. Std. Err. z P>|z|

-----+-----  
 female | 1.403022 .3671964 3.82 0.000 .6833301 2.122713

read | .1411402 .0224042 6.30 0.000 .0972287 .1850517

\_cons | -7.798179 1.235685 -6.31 0.000 -10.22008

-5.376281

---

The first line of syntax below runs the second model, that is, the model with all four predictor variables. The second line of code stores the value of the log likelihood for the model (-84.4), which is temporarily stored as the returned estimate (e(II) ), in the scalar named m2. Again, we won't say much about the output except to note that the coefficients for both math and science are both statistically significant. So we know that, individually, they are statistically significant predictors of hiwrite.

```
logit hiwrite female read math science  
scalar m2 = e(II)
```

```
Iteration 0: log likelihood = -137.41698
```

```
Iteration 1: log likelihood = -90.166892
```

```
Iteration 2: log likelihood = -84.909776
```

```
Iteration 3: log likelihood = -84.42653
```

```
Iteration 4: log likelihood = -84.419844
```

```
Iteration 5: log likelihood = -84.419842
```

**Logistic regression Number of obs = 200**

**LR chi2(4) = 105.99**

**Prob > chi2 = 0.0000**

**Log likelihood = -84.419842 Pseudo R2 = 0.3857**

-----  
**hiwrite | Coef. Std. Err. z P>|z|**  
 -----+-----

|         |           |          |       |       |           |           |
|---------|-----------|----------|-------|-------|-----------|-----------|
| female  | 1.805528  | .4358101 | 4.14  | 0.000 | .9513555  | 2.6597    |
| read    | .0529536  | .0275925 | 1.92  | 0.055 | -.0011268 | .107034   |
| math    | .1319787  | .0318836 | 4.14  | 0.000 | .069488   | .1944694  |
| science | .0577623  | .027586  | 2.09  | 0.036 | .0036947  | .1118299  |
| _cons   | -13.26097 | 1.893801 | -7.00 | 0.000 | -16.97275 | -9.549188 |

-----

Now that we have the log likelihoods from both models, we can perform a likelihood ratio test.

The first line of syntax below calculates the likelihood ratio test statistic. The second line of syntax below finds the p-value associated with our test statistic with two degrees of freedom. Looking below we see that the test statistic is 36.05, and that the

associated p-value is very low (less than 0.0001). The results show that adding math and science as predictor variables together (not just individually) results in a statistically significant improvement in model fit. Note that if we performed a likelihood ratio test for adding a single variable to the model, the results would be the same as the significance test for the coefficient for that variable presented in the above table.

```
di "chi2(2) = " 2*(m2-m1)
di "Prob > chi2 = "chi2tail(2, 2*(m2-m1))
```

```
chi2(2) = 36.050677
Prob > chi2 = 1.485e-08
```

Using Stata's postestimation commands to calculate a likelihood ratio test

As you have seen, it is easy enough to calculate a likelihood ratio

test "by hand." However, you can also use Stata to store the estimates and run

the test for you. This method is easier still, and

probably less error prone. The first line of syntax runs a logistic regression model, predicting hiwrite based on students' gender (female), and reading scores (read). The second line of syntax asks Stata to store the estimates from the model we just ran, and instructs Stata that we want to call the estimates m1.

It is necessary to give the estimates a name, since Stata allows users to store the estimates from more than one analysis, and we will be storing more than one set of estimates.

use

[https://stats.idre.ucla.edu/stat/stata/faq/nested\\_tests](https://stats.idre.ucla.edu/stat/stata/faq/nested_tests),

clear

logit hiwrite female read

estimates store m1

Below is the output. Since it is not our primary concern here, we will skip the interpretation of the logistic regression model. Note

that storing the estimates does not produce any output.

```
Iteration      0:      log      likelihood      =
-137.41698-137.41698-137.41698
Iteration 1: log likelihood = -104.79885
Iteration 2: log likelihood = -102.52269
Iteration 3: log likelihood = -102.44531
Iteration 4: log likelihood = -102.44518
```

Logistic regression Number of obs = 200

LR chi2(2) = 69.94

Prob > chi2 = 0.0000

Log likelihood = -102.44518 Pseudo R2 = 0.2545

```
-----
hiwrite | Coef. Std. Err. z P>|z|
-----+-----
female | 1.403022 .3671964 3.82 0.000 .6833301 2.122713
read | .1411402 .0224042 6.30 0.000 .0972287 .1850517
_cons | -7.798179 1.235685 -6.31 0.000 -10.22008
-5.376281
-----
```

The first line of syntax below this paragraph runs the second model, that is

the model with all four predictor variables. The second line of syntax saves the estimates from this model, and names them m2. Below the syntax is the output generated. Again, we won't say much about the output except to note that the coefficients for both math and science are both statistically significant. So we know that, individually, they are statistically significant predictors of hiwrite. The tests below will allow us to test whether adding both of these variables to the model significantly improves the fit of the model, compared to a model that contains just female and read.

```
logit hiwrite female read math science  
estimates store m2
```

```
Iteration 0: log likelihood = -137.41698
```

```
Iteration 1: log likelihood = -90.166892
```

```
Iteration 2: log likelihood = -84.909776
```

```
Iteration 3: log likelihood = -84.42653
```

```
Iteration 4: log likelihood = -84.419844
```

```
Iteration 5: log likelihood = -84.419842
```

```
Logistic regression Number of obs = 200
```

**LR chi2(4) = 105.99**

**Prob > chi2 = 0.0000**

**Log likelihood = -84.419842 Pseudo R2 = 0.3857**

-----  
**hiwrite | Coef. Std. Err. z P>|z|**  
 -----+-----

|                |                    |                 |              |              |                  |                  |
|----------------|--------------------|-----------------|--------------|--------------|------------------|------------------|
| <b>female</b>  | <b>  1.805528</b>  | <b>.4358101</b> | <b>4.14</b>  | <b>0.000</b> | <b>.9513555</b>  | <b>2.6597</b>    |
| <b>read</b>    | <b>  .0529536</b>  | <b>.0275925</b> | <b>1.92</b>  | <b>0.055</b> | <b>-.0011268</b> | <b>.107034</b>   |
| <b>math</b>    | <b>  .1319787</b>  | <b>.0318836</b> | <b>4.14</b>  | <b>0.000</b> | <b>.069488</b>   | <b>.1944694</b>  |
| <b>science</b> | <b>  .0577623</b>  | <b>.027586</b>  | <b>2.09</b>  | <b>0.036</b> | <b>.0036947</b>  | <b>.1118299</b>  |
| <b>_cons</b>   | <b>  -13.26097</b> | <b>1.893801</b> | <b>-7.00</b> | <b>0.000</b> | <b>-16.97275</b> | <b>-9.549188</b> |

-----

The first line of syntax below tells Stata that we want to run an lr test, and that we want to compare the estimates we have saved as m1 to those we have saved as m2. The output reminds us that this test assumes that

A is nested in B, which it is. It also gives us the chi-squared value for the test (36.05) as well as the p-value for a chi-squared of 36.05 with two degrees of freedom. Note that the degrees of freedom for

the lr test, along with the other two tests, is equal to the number of parameters that are constrained (i.e., removed from the model), in our case, 2. Note that the results are the same as when we calculated the lr test by hand above. Adding math and science as predictor variables together (not just individually) results in a statistically significant improvement in model fit.

As noted when we calculated the likelihood ratio test by hand, if we performed a likelihood ratio test for adding a single variable to the model, the results would be the same as the significance test for the coefficient for that variable presented in the table above.

**lrtest m1 m2**

**Likelihood-ratio test LR chi2(2) = 36.05**

**(Assumption: A nested in B) Prob > chi2 = 0.0000**

The entire syntax for a likelihood ratio test, all in one block, looks like this:

**logit hiwrite female read**

**estimates store m1**

```
logit hiwrite female read math science
estimates store m2
lrtest m1 m2
```

### Example of a Wald test

As was mentioned above, the Wald test approximates the LR test, but with the advantage that it only requires estimating one model. The Wald test works by testing that the parameters of interest are simultaneously equal to zero. If they are, this strongly suggests that removing them from the model will not substantially reduce the fit of that model, since a predictor whose coefficient is very small relative to its standard error is generally not doing much to help predict the dependent variable.

The first step in performing a Wald test is to run the full model (i.e., the model containing all four predictor variables). The first line of syntax below does this (but uses the quietly prefix so that the output from the regression is not shown). The second line of syntax below instructs Stata to run a Wald test in order to test whether the coefficients for the variables

**math and science**

**are simultaneously equal to zero. The output first gives the null hypothesis.**

**Below that we see the chi-squared value generated by the Wald test, as well as**

**the p-value associated with a chi-squared of 27.53 with two degrees of freedom.**

**Based on the p-value, we are able to reject the null hypothesis, again**

**indicating that the coefficients for math and science are not simultaneously equal to zero,**

**meaning that including**

**these variables create a statistically significant improvement in the fit of the model.**

**quietly: logit hiwrite female read math science**

**test math science**

**( 1) math = 0**

**( 2) science = 0**

**chi2( 2) = 27.53**

**Prob > chi2 = 0.0000**