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Econometrics
Hypothesis tests

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- **t-test**

Tests the significance of <u>only one</u> coefficient in a regression.

Computed t-value $= \dfrac{\hat{\beta} - B_{Ho}}{SE(\hat{\beta})}$

Tests whether the true coefficient, β, is equal to a hypothesized value, B_{Ho} (zero, in most cases). Compare this t-value to the critical t-value, found in all econometrics books. If the <u>absolute t-value</u> is greater than the critical one, for some chosen level of significance (usually 1, 5 or 10%), the null hypothesis can be rejected.

  -Use a <u>two-sided</u> critical t-value if: Ho: β=0 and Ha: $\beta \neq 0$.

  -Use a <u>one sided</u> critical t-value if:

                Ho:$\beta \geq 0$ and Ha: β<0 This means you expect a negative coefficient

            or Ho: $\beta \leq 0$ and Ha:β>0 when you expect a positive coefficient.

The <u>degrees of freedom</u> = n-1-k, where n is the number of observations and k is the number of (slope) independent variables.

t-test does not test theoretical validity nor does the t-test indicate importance.

- **p-value**

Most econometric packages provide the p-value (for a **TWO-sided test**), or probability (in EViews), for each and every test. The p-value tells us the lowest level of significance at which the null-hypothesis could be rejected. It can also be thought of as the probability of the null-hypothesis being true. For ONE-sided test, divide p-value by 2.

- **F-test**

Tests whether all or some estimated coefficients are <u>jointly</u> equal to a hypothesized value (zero, usually). In a regression:

    Y=b0 + b1X1 + b2X2 + b3X3 + u

    we could use F-test to test: (i) $\beta_1 = \beta_2 = \beta_3 = 0$ or (ii) $\beta_1 = \beta_2 = 0$ or (iii) $\beta_1 = \beta_2$.

<u>Joint test on all coefficients.</u>

Most regression packages and excel automatically compute the F-value for (i), i.e. it tests the null hypothesis: all coefficients (excluding the constant) are jointly equal to zero. The alternative hypothesis is the null is not true. Critical F-values are reported in all econometrics books and if the computed F-value is greater than the critical F-value, the null hypothesis is rejected.

$F_{(k,\ n-k-1)}$ value $= \dfrac{ESS/k}{RSS/(n-k-1)}$

where ESS is the explained (by regression) sum of squares, RSS is the Residual Sum of Squares, k is the number of independent variables (excluding the constant, thus, the -1) and n is the number of observations.

Notice how the F-value closely resembles $R^2 = \dfrac{ESS}{TSS}$

<u>Joint test on a subset of coefficients</u> (pp. 163-166)

We can also compute the F-value to test (ii) and (iii). To test (ii), run two regressions:

1. Y=b0 + b1X1 + b2X2 + b3*X3 + u   -unrestricted regression

2. Y=b0 + b3*X3 + u2   -restricted regression (2 restrictions: b1=b2=0)

Then we test the Sum of Squares from each regression:

$$F_{(m,\ n-k-1)}\text{-value} = \frac{(RSS_R - RSS_{UR})/m}{RSS_{UR}/(n - k - 1)}$$

where RSS_R is the RSS from the restricted equation, RSS_{UR} is the RSS from the unrestricted one, m is the number of restrictions (in this case we are testing two coefficients jointly, thus, m is 2).

- **More on F-tests**

Testing for coefficient constancy: Chow Test and Dummy variables.

The F-test can also be applied to test if coefficients have changed between sample periods. Consider the regression Y=b0+b1X1 + u   which is estimated using (time series) data from 1950-2000. If we think the b1 coefficient changed after 1970 we can run two separate regressions (using two data samples):

Y=b0+b2X1 + u2   using 1950-1970 data
Y=b0+b3X1 + u3   using 1971-2000 data

we can then use the CHOW test (p.151; pp. 221-224 Gujarati)) to test if $\beta_2 = \beta_3$, i.e. the effect of X1 on Y is the same in each sample.

There is a relatively easier way to test whether the two coefficients are equal which involves creating dummy variables (pp. 225-229). Dummy variables are added to the regression (and only one regression is estimated, rather than two) as additional independent variables (intercept dummies and slope dummies) and their significance is then judged by applying t-test on each dummy coefficient.

- **Durbin-Watson d-test for serial correlation**

Serial correlation in the residuals is likely to arise in time-series data. (does not bias the coefficients but affects their standard errors and, consequently, their t-values). An example of a first order serial correlation is:

$u_t = p*u_{t-1} + v_t$

where u is the residuals from a regression.

EViews automatically reports the Durbin-Watson (DW) test statistic in the regression output. Here is how the DW is computed:

$$\frac{\sum_{2}^{n}(u_t - u_{t-1})^2}{\sum_{1}^{n}(u_t)^2}$$

A DW value around 2 indicates no serial correlation, i.e. we cannot reject the Ho: p=0. All econometrics books report the critical DW test statistics (upper and lower bounds).

- **Test for heteroskedasticity**

Heteroskedasticity, where the variance of the residual is not constant, is likely to be present in cross-section data (redefining the data is sometimes useful in eliminating the heteroskedasticity, such as dividing GDP by population in international cross-section data). The estimated coefficients are still unbiased but the estimated variance is not correct (OLS assumes it is constant), affecting standard errors of the coefficients and their t-values. Thus, the presence of heteroscedasticity makes the t-values unreliable.

Sometimes a visual inspection of the residuals indicates a clear presence of heteroskedasticity. In other cases we must test specifically for this. The Park test and the White-test are two of many tests that can be used. EViews can implement the White-test very easily.

Park test

This test assumes the form of heteroskedasticity is known. However, in many cases we do not know this.

White -test

This test assumes we do not know the exact form of heteroscedasticity.

If you run the following regression: $Y = b0 + b1X1 + b2X2 + b3*X3 + u$ and you want to test if the residuals, u, are homoscedastic, you have to run another regression, where u^2 is your dependent variable and the independent variables would include X1, X2,X3, and square values of X1, X2 X3 in addition to cross products of the Xs (X1*X2, X1*X3 and X2*X3). A constant should also be added:

$u^2 = a0 + a1X1 + a2X2 + a3X3 + a4(X1)^2 + a5(X2)^2 + a6(X3)^2 + a7(X1*X2) + a8(X1*X3) + a9(X2*X3) + v$

Then the test statistics is

$$\chi_s^2 = \mathbf{n*R^2}$$

where n is the number of observations and s (the degrees of freedom) is the number of independent variables in the regression ($s = \dfrac{k^2 - k}{2} + 2k$). For the regression above, s is 9 and the computed Chi-square value should be compared to the critical one, for 9 d.f.

      H_o: variance of u is homoskedastic
      H_a: variance of u is heteroskedastic.

If the computed Chi-square is greater than the critical one, reject Ho.

The White-test can be done in **EViews:**
   Select **View/Residual Diagnostics/Heteroskedasticity Tests** and select **'White'**
     Note: EViews also provides F-statistic to test the H_0 and p-values (for the F and χ^2).

Heteroskedasticity adjusted standard errors.

If you find the residuals to be heteroskedastic, the standard errors must be adjusted.

To do this in **EViews:**
   When you type the regression in EViews, click the **OPTIONS** tab, select **'HAC (Newey-West)'** under the **'Coefficient covariance matrix'**.
   OR
   if you have estimated the regression already, use **PROC/Specify Estimate** and select **'HAC (Newey-West)'** under the **'Coefficient covariance matrix'**.