Chapter 7: Specification: Choosing A Functional Form

In this chapter:

UE section 7.2 presents alternative functional forms that are useful when specifying econometric models. Linear models are frequently too restrictive to properly fit the functional form suggested by the underlying theory.

The last column of Table 7.1 below shows the correct EViews specification for the alternative functional forms printed in *UE*, Table 7.1, p. 214. You can use the table as a guide, but you must realize that Y represents the dependent variable while X_1 & X_2 represent the only independent variables in all of the equations/specifications. Note that a constant (C) should be included in all models even if theory suggests otherwise (see *UE*, p. 201). You must have a workfile open in order to specify and estimate a regression model. Then, to specify a regression model in EViews, select **Objects/New Object/Equation** from the workfile menu and enter the appropriate ***EViews specification*** (see the last column of the table below), in the Equation Specification: window.[1]

Table 7.1: EViews Specification of Functional Forms

Section	*Equation #*	*Fcn. Form*	*Equation specification*	*EViews specification*
7.2.1	----	Linear	$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2$	Y C X1 X2
7.2.2	7.3	Double-Log	$\ln Y = \beta_0 + \beta_1 \ln X_1 + \beta_2 \ln X_2$	log(Y) C log(X1) log(X2)
7.2.3	7.7	Lin-Log	$Y = \beta_0 + \beta_1 \ln X_1 + \beta_2 X_2$	Y C log(X1) X2
7.2.3	7.9	Log-Lin	$\ln Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2$	log(Y) C X1 X2
7.2.4	7.10	Polynomial	$Y = \beta_0 + \beta_1 X_1 + \beta_2 (X_1^2) + \beta_3 X_2$	Y C X1 X1^2 X2
7.2.5	7.13	Inverse	$Y = \beta_0 + \beta_1 (1/X_1) + \beta_2 X_2$	Y C 1/X1 X2
7.5	7.20	Dummy*	$Y = \beta_0 + \beta_1 X_1 + \beta_2 D_1$	Y C X1 D1
7.5	7.22	Dummy**	$Y = \beta_0 + \beta_1 X_1 + \beta_2 D_1 + \beta_3 D_1 X_1$	Y C X1 D1 D1*X1

* Intercept dummy variable. ** Intercept and slope dummy variables.

Calculating "Quasi - R^2" in EViews (*UE* 7.3.1, footnote 5, p. 215):

The dependent variable must be in the same form when using R^2 and adjusted R^2 to compare the overall goodness of fit between two equations. For example, it would not be appropriate to compare the R^2 for a linear model with a double-log or a log-lin model. However, it would be appropriate to compare R^2 for a linear model with a lin-log, a

[1] Alternately, select **Quick/Estimate Equation** from the main menu. If this method is used you must name the equation to save it. Select **Name** on the equation menu bar and enter the desired name in the Name to identify object: window, and click **OK**.

polynomial, or an inverse functional form model. Likewise, it would be appropriate to compare R^2 for double-log and log-lin functional form models. In order to demonstrate the process, the car acceleration data introduced in *UE*, Exercise 16, p. 234, will be used to demonstrate the process of calculating the quasi-R^2. The steps below show how to compare the goodness of fit for models using S (the number of seconds it takes a car to accelerate from 0 to 60 miles per hour) as the dependent variable versus using the natural log of S as the dependent variable. In both models, the independent variables are the same as the original model printed at the top of *UE*, p. 236.

Calculating "Quasi - R^2" for a linear versus a log-lin model using EViews:

Step 1. Open the EViews workfile named *Cars7.wk1*.

Step 2. Select **Objects/New Object/Equation** on the workfile menu bar, enter *S C T E P H* in the Equation Specification: window, and click **OK**.

Step 3. Select **Name** on the equation menu bar, write *linear* in the Name to identify object: window, and click **OK**. Minimize the equation object named *linear*.

Step 4. Select **Objects/New Object/Equation** on the workfile menu bar, enter *log(S) C T E P H* in the Equation Specification: window (i.e., the log-lin functional form), and click **OK**.

Step 5. Select **Name** on the equation menu bar, write *loglin* in the Name to identify object: window, and click **OK**.

Step 6. Select **Forecast** on the equation menu bar, select *S* in the Forecast of:[2] window, enter *SF* in the Forecast name: window, uncheck the two boxes in the Output: window (the only objective here is to create a forecast series, not a forecast evaluation), and click **OK**. A new series named *SF* appears in the workfile window.

Steps 7, 8 & 9 calculate the quasi-R^2 for this regression (*UE* 7.3.1, footnote 5, p. 215).

Step 7. Minimize the equation window, select **Genr** on the workfile menu bar, type *numerator=(S-SF)^2* in the Enter equation: window, and click **OK** (this step generates the un-summed variable in the numerator of the quasi-R^2 equation).

Step 8. Select **Genr** on the workfile menu bar, type *denominator=(S-@mean(S))^2* in the Enter equation: window, and click **OK** (this step generates the un-summed variable in the denominator of the quasi-R^2 equation).

Step 9. To calculate the quasi-R^2, type the following equation in the command window and press **Enter**: *scalar quasir2=1-(@sum(numerator)/@sum(denominator))*. A new variable named *quasir2* will appear in the workfile window. Double click on it and the value for the quasi-R^2 will be displayed in the lower left of the screen (0.783958974). The quasi-R^2 calculated in **Step 9** (i.e., 0.78) is in-between the R^2 from the linear model estimated in **Step 2** (i.e., 0.71) and the R^2 from the log-lin model estimated in **Step 5** (i.e., 0.81).

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[2] The **Forecast** procedure in EViews gives you the option of forecasting the transformed dependent variable (i.e., *LOG(S)* in this case) or the original variable (i.e., *S* in this case). Select S, since the computation of quasi-R^2 requires converting of *LOG(S)* to *S* by taking the anti-log of the dependent variable (this can also be done by using the EViews command *@exp(LOG(S))*.

Coefficient restrictions tests using EViews (*UE*, Appendix 7.7):

The F-test can be used to test a wide range of hypothesis concerning regression coefficients. For example, suppose that the claim was made that when a car has a manual transmission it increases its acceleration speed (i.e., decreases the number of seconds it takes to accelerate from 0 to 60 miles per hour) just as much as adding 100 horsepower to the car. Translating this into the language of *UE*, Equation 7.28, p. 235, this means that the absolute value of the coefficient on T_i is 100 times larger than the absolute value of the coefficient on H_i. Just looking at the size of the estimated coefficients, it appears that you can easily reject the hypothesis because the absolute value of the coefficient on T_i is only about 41.5 times larger than the absolute value of the coefficient on H_i (divide the coefficient on T_i by the coefficient on H_i). However, these coefficients are just estimates. Follow these steps to carry out an F-test for the null hypothesis that the absolute value of the coefficient on T_i is 100 times larger than the absolute value of the coefficient on H_i. :

Step 1. Open the EViews workfile named *Cars7.wk1*.
Step 2. Select **Objects/New Object/Equation** on the workfile menu bar, enter *S C T E P H* in the Equation Specification: window, and click **OK**.
Step 3. Select **Name** on the equation menu bar, write *EQ01* in the Name to identify object: window, and click **OK**.
Step 4. Select **View/Coefficients Tests/Wald-Coefficient Restrictions …** on the equation menu bar, enter *-C(2)=-100*C(5)* in the Coefficients separated by commas: window, and click **OK** to reveal the following output:[3]

Wald Test:
Equation: EQ01

Null Hypothesis:	-C(2)=-100*C(5)		
F-statistic	2.485049	Probability	0.124472
Chi-square	2.485049	Probability	0.114933

The null hypothesis is *-C(2)=-100*C(5)*, since variable T is the second coefficient and variable H is the fifth coefficient in the EViews Estimation Output from **Step 2**. The F-statistic compares the residual sum of squares computed with and without the restrictions imposed. If the restrictions are valid, there should be little difference in the two residual sum-of-squares and the F-value should be small. Based on the Wald Test: results table, the null hypothesis cannot be rejected at the 5% level of significance. The calculated F-statistic of *2.49* is less than the critical F-value of *4.14*. The critical F-value can be found in *UE*, Table B-2, p. 609 for 1 degree of freedom in the numerator and 33 (interpolate between the 30 and 40) degrees of freedom in the denominator or EViews can calculate

[3] The coefficients should be referred to as C(1), C(2), and so on (do not use series names). Multiple coefficient restrictions must be separated by commas and the restrictions should be expressed as equations involving estimated coefficients and constants. The coefficients should be referred to as C(1), C(2), and so on (do not use series names).

its value.[4] The reported probability is the marginal significance level of the F-test. It supports this result in that rejecting the null hypothesis would be wrong less than 12.44% of the time.

The Chi-square statistic is equal to the F-statistic times the number of restrictions under test. In this example, there is only one restriction and so the two test statistics are identical with the p-values of both statistics indicating that we cannot reject the null hypothesis, that the absolute value of the coefficient on T_i is 100 times larger than the absolute value of the coefficient on H_i, at the 10% significance level. The 10% significance critical value for the χ^2 test can be found in *UE*, Table B-8, p. 619 to be 2.71.

The *Chow test*, alternately termed Chow's Breakpoint Test (*UE*, Appendix 7.7):

Chow's Breakpoint Test divides the data into two sub-samples.[5] It then estimates the same equation for each sub-sample separately, to see whether there are significant differences in the estimated equations. A significant difference indicates a structural change in the relationship.

Follow these steps to apply the Chow breakpoint test, as described in *UE*, pp. 241-242, to determine whether there was a structural change in the demand for chicken in 1976:

Step 1. Open the EViews workfile named *Chick6.wf1*.
Step 2. Select **Objects/New Object/Equation** on the workfile menu bar, enter *Y C PC PB YD* in the Equation Specification: window, and click **OK**.
Step 3. Select **Name** on the equation menu bar, write *EQ01* in the Name to identify object: window, and click **OK**.
Step 4. Select **View/Stability Tests/Chow Breakpoint Test…** on the equation menu bar, enter *1976* in the Enter one date (observation) for the Forecast Test or one or more dates for the Breakpoint Test: window, and click **OK** to reveal the following output:

Chow Breakpoint Test: 1976

F-statistic	4.542962	Probability	0.004498
Log likelihood ratio	17.98027	Probability	0.001245

EViews reports two test statistics for the Chow breakpoint test. The F-statistic is based on the comparison of the restricted and unrestricted sum of squared residuals. EViews calculates the F-statistic using the formula printed in *UE*, Equation 7.36, p. 242. In this

[4] To have EViews calculate the 5% critical F-value for this problem, type the following equation in the command window *=@qfdist(0.95,1,eq01.@regobs-eq01.@ncoefs)*, press **Enter** and view the following value on the status bar in the lower left of the screen Scalar = 4.13925249556. For the 10% critical F-value type *=@qfdist(0.90,1,eq01.@regobs-eq01.@ncoefs)* in the command window, and press **Enter** and view the following value on the status bar in the lower left of the screen Scalar = 2.86408341558.
[5] One major drawback of the breakpoint test is that each sub-sample requires at least as many observations as the number of estimated parameters. This may be a problem if, for example, you want to test for structural change between wartime and peacetime where there are only a few observations in the wartime sample.

case, the calculated F-statistic of 4.54 exceeds the critical F-value of 2.63 for the 5% level of significance so the null hypothesis of no structural change can be rejected. The critical F-value can be found in *UE*, Table B-2, p. 609 for 4 degrees of freedom in the numerator and 36 (interpolate between the 30 and 40) degrees of freedom in the denominator or EViews can calculate its value.[6] The reported probability is the marginal significance level of the F-test. It supports this result in that rejecting the null hypothesis would be wrong less than 0.4498% of the time.

The log likelihood ratio statistic is based on the comparison of the restricted and unrestricted maximum of the log likelihood function. The LR test statistic has an asymptotic χ^2 distribution with degrees of freedom equal to (m-1)*(k+1) under the null hypothesis of no structural change, where m is the number of sub-samples and k is the number of independent variables in the model (i.e., m = 2 in this case because one breakpoint is selected and k = 3). The calculated value for LR test statistic of 17.98 exceeds of 9.49 for the 5% level of significance and 13.28 for the 1% level of significance so the null hypothesis of no structural change can be rejected.[7] The reported probability is the marginal significance level of the χ^2 test. It supports this result in that rejecting the null hypothesis would be wrong less than 0.1245% of the time.

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[6] To have EViews calculate the 5% critical F-value for this problem, type the following equation in the command window *=@qfdist(0.95,eq01.@ncoef,eq01.@regobs-2*eq01.@ncoef)*, press **Enter** and view the following value on the status bar in the lower left of the screen Scalar = 2.63353209421.

[7] The critical value for the χ^2 test can be found in *UE*, Table B-8, p. 619.