This assignment is based on the dairy farms data used in the class demonstrations. Though they are a panel of 247 farms observed in 6 years, for present purposes, we will treat them as a cross section.

1. After loading the dairy.lpj project file, we define some namelists with

   NAMELIST ; COBBDGLS = ONE,X1,X2,X3,X4 $
   NAMELIST ; TRANSLOG = COBBDGLS,
   X11,X22,X33,X44,X12,X13,X14,X23,X24,X34 $
   NAMELIST ; TIME = YEAR93,YEAR94,YEAR95,YEAR96,YEAR97 $

We fit a Cobb-Douglas production function by least squares with the command

   \textbf{REgress ; LHS = YIT ; RHS = COBBDGLS $}

To obtain a robust, White heteroscedasticity corrected covariance matrix for the least squares estimates, it is only necessary to add ;HETEROSCEDASTICITY or just ;HET to the regression command. This will replace the conventional covariance estimator with the White estimator. It will also report a Breusch and Pagan LM statistic for testing for heteroscedasticity.

a. Reestimate the model with the White correction. Do the standard errors differ much from the OLS standard errors?

b. What is the result of the LM test for heteroscedasticity?

2. In order to use least absolute deviations (LAD) estimator instead of OLS, the \textbf{REgress} command is changed by adding ;ALG = LAD. (Omit the ;HET parameter for this estimator.) In addition, the standard errors must be computed using bootstrapping. You must specify the number of bootstrap replications. Use ;NBT=the number, for example ;NBT = 25. Fit the Cobb-Douglas model using LAD instead of OLS, with at least 25 bootstraps. Do the results differ much from OLS?

The theory of the LAD estimator is that in the model, $\beta'x$ provides the median, i.e., the 50$^{th}$ percentile of the distribution of $y|x$. It might be interesting to see how the production function behaves around other quantiles. That is, suppose we model the production function a bit less parametrically as $y = \beta(q)'x + \epsilon$, where $q$ denotes a quantile of the distribution. Then, the regression above would be $y = \beta(.5)'x + \epsilon$. You can try different quantiles, and see if the parameter estimates change by using

   \textbf{QREG ; LHS = YIT ; RHS = COBBDGLS ; Qnt = the quantile $}

For example, with ;Qnt = .5, you get the same results as \textbf{REgress} with ;Alg=LAD. Try a few different quantiles, and see if the parameter estimates do change as $q$ changes.
3. We want to test for the presence of ‘time’ effects in the Cobb-Douglas model. The class example showed how to test the translog model against the Cobb-Douglas.
   a. Adapt that procedure to test for the joint significance of the 5 time dummy variables in the model

   \[
   \text{REGRESS} \; ; \; \text{LHS} = \text{YIT} \; ; \; \text{RHS} = \text{TIME,COBDGLS}$
   \]

   What is the result of the test? Are the 5 dummy variables jointly significant?

   b. The Wald test is another way to test the joint significance of a set of variables. You can do this with matrix algebra. The Wald statistic is

   \[
   W = (b - \beta^0)' [\text{Var}(b)]^{-1} (b - \beta^0)
   \]

   where \( b \) is the estimate, \( \beta^0 \) is the hypothesized value, and \( \text{Var}(b) \) is the estimated covariance matrix. In this case, \( b \) is the first 5 coefficients in the model and \( \beta^0 \) is 0. The matrix commands you can use after fitting the model by OLS are

   \[
   \text{MATRIX} \; ; \; \text{BT} = \text{B}(1:5) \; ; \; \text{VT} = \text{VARB}(1:5,1:5) \; ; \; \text{LIST} \; ; \; W = \text{BT}'<\text{VT}>\text{BT}$
   \]

   The result is a chi-squared statistic with 5 degrees of freedom. Is the result larger than the critical value? The last line of the example in class shows how to compute the critical value from the chi-squared table. Carry out the test.

4. We now want to use matrix algebra to carry out the Wald test for the translog model against the Cobb-Douglas model, with time effects included. If you use

   \[
   \text{REGRESS} \; ; \; \text{LHS} = \text{YIT} \; ; \; \text{RHS} = \text{TRANSLOG,TIME}$
   \]

   the coefficients you wish to test the joint significance of are the 6th to 15th (of 20 in the equation). Use the three procedures developed earlier to test for the joint significance of the second order coefficients in the model.

5. We now wish to test the hypothesis of a linear restriction on the model coefficients. We will test for constant returns to scale in the Cobb-Douglas model. In the model

   \[
   \text{REGRESS} \; ; \; \text{LHS} = \text{YIT} \; ; \; \text{RHS} = \text{One,X1,X2,X3,X4}$
   \]

   the hypothesis is that the four input coefficients sum to 1. The easiest way to carry out the test is to let the program do it for you by computing the constrained regression. Use

   \[
   \text{REGRESS} \; ; \; \text{LHS} = \text{YIT} \; ; \; \text{RHS} = \text{One,X1,X2,X3,X4}$
   \; ; \; \text{CLS} : \; \text{b(2)} + \text{b(3)} + \text{b(4)} + \text{b(5)} = 1$
   \]

   The regression results will contain an F statistic. Carry out the test. What do you conclude? Another way to use LIMDEP to do this test is to use the WALD command (which is very general – we’ll use the simplest possible form).

   \[
   \text{REGRESS} \; ; \; \text{LHS} = \text{YIT} \; ; \; \text{RHS} = \text{One,X1,X2,X3,X4}$
   \; \; \text{WALD} : \; \text{Fn1} = \text{b_X1+b_X2 + b_X3 + b_X4} - 1$
   \]
Carry out the test. What is the result? (Note, the WALD command is based on the previous regression. A more general form that is based on a parameter vector estimate and a covariance matrix, for this test, would be

```
WALD ; Start = B ; Var = VARB ; Labels = b0,b1,b2,b3,b4
; Fn1 = b1+b2+b3+b4 – 1 $
```

which will give the identical result. You can use any other functions of the parameters you like.

6. We will now analyze the least squares residuals for evidence of nonnormality. We need first to compute them. There are two ways:

```
REGRESS ; LHS = YIT ; RHS = COBBDGLS ; RES = u $
```

or, after the REGRESS command, use

```
CREATE ; u = YIT – COBBDGLS’B $  
```

(Note how the different parts of the program interact.) With the residuals in hand, first look at the distribution by estimating it with a kernel density estimator. Use

```
KERNEL ; RHS = U $
```

Does it appear to be asymmetric. Now, we can use a chi-squared sort of statistic to ‘test’ for nonnormality. The test is based on the third and 4th moments of the residuals – they should be 0 and 3, respectively. The test statistic is

```
C  = N × [ (m3/su3)^2 / 6   +   (m4/su4 – 3)^2 /24 ]
```

where N is the sample size, su is the standard deviation of the residuals and m3 and m4 are the third and fourth sample moments. (We can’t use the name ‘s’ because like ‘B’ and ‘VARB’ it is a program reserved name.) After obtaining the residuals as above, you can compute the parts with the following

```
CREATE ; U2 = u*u ; U3 = U2*u ; U4 = U2*U2 $ 
CALC      ; su = sqr ( xbr ( u2 )) ;  m3 = xbr( u3 ) ; m4 = xbr ( u4) $ 
CALC      ; List ; C = N *(( m3/su^3)^2 / 6   +   (m4/su^4 – 3)^2 /24 )  $ 
```