Logan Albiani

12/9/18

Prof. Siegler

ECN 102

Homework #4

1. **Linear Restrictions, the Cobb-Douglas Production Function, and Constant Returns to Scale**
   1. ***Using the lm command in R, estimate the unrestricted model above using OLS and report the results using stargazer.***

===============================================

Dependent variable:

---------------------------

lnY

-----------------------------------------------

lnK 0.815\*\*\*

(0.033)

lnL 0.202\*\*\*

(0.035)

Constant 0.880\*\*

(0.403)

-----------------------------------------------

Observations 73

R2 0.981

Adjusted R2 0.980

Residual Std. Error 0.261 (df = 70)

F Statistic 1,796.778\*\*\* (df = 2; 70)

===============================================

Note: \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

* 1. ***The constant returns to scale restriction under H0 can now be imposed to derive the restricted model. Use stargazer to report the results of this estimated restricted moel.***

===============================================

Dependent variable:

---------------------------

lnYL

-----------------------------------------------

lnKL 0.810\*\*\*

(0.033)

Constant 0.971\*\*

(0.392)

-----------------------------------------------

Observations 73

R2 0.897

Adjusted R2 0.895

Residual Std. Error 0.261 (df = 71)

F Statistic 617.440\*\*\* (df = 1; 71)

===============================================

Note: \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

* 1. ***Compute and interpret the appropriate F-test for constant returns to scale.***

F = [(RSSR-RSSU)/q]/[RSSU/(n-k)]

F = [(4.821-4.753)/1]/[4.753/(73-3)]

F = .068/.067

F = .994

Fq,n-k = 2.77

Given that our F-statistic, .994, is less than the critical value of 2.77, we fail to reject the null hypothesis. Therefore, we can conclude that all of the classical assumptions hold and that this model is the best linear unbiased estimator.

As for the p-value, we see that the probability of this linear model predicting these particular production outputs is .322. Given that we’re evaluating the linear model at a 10% confidence level, we can see that .322 is less .9, thus meaning again that we fail to reject the null hypothesis. This similarly means that the classical assumptions hold and that the linear model is the best linear unbiased estimator for production.

1. **Multiple Regression and Model Specification**
   1. ***Estimate the unrestricted model using OLS with R, report the results with stargazer***

===============================================

Dependent variable:

---------------------------

lnprice

-----------------------------------------------

lnestimate 0.880\*\*\*

(0.102)

bdrms 0.004

(0.018)

bathrms -0.003

(0.026)

lnsqrft -0.086

(0.083)

lnlotsize 0.062

(0.039)

age -0.001

(0.001)

pool 0.002

(0.029)

central 0.008

(0.035)

Constant 1.756\*\*

(0.859)

-----------------------------------------------

Observations 44

R2 0.962

Adjusted R2 0.953

Residual Std. Error 0.055 (df = 35)

F Statistic 109.516\*\*\* (df = 8; 35)

===============================================

Note: \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

* 1. ***Test olsu for regression misspecification using RESET, Jarque-Bera normality, and the Breusch Pagan test for heteroscedasticity.***

When conducting the Ramsey RESET Test, we’re testing for functional misspecification. From the resulting critical value which was produced by R, we can see that it is equal to 1.7047. Conducting an F test to calculate the F-statistic for our given linear model results in an F-value of .56. Clearly, .56 is less than 1.7047, therefore, we fail to reject the null hypothesis that our linear model has baked in it a general misspecification.

As for the Jarque-Bera test, we will be testing for the normality in the distribution of our residuals. We do this by testing to see whether or not our linear model fits a chi-squared distribution. The only manners in which it would not or if it has excessive skewness, excessive kurtosis, or both. Our results, as per R, come out to be a p-value of .611 and a chi-squared value of .9853. Neither of these values represent a statistically significant finding, therefore, we can conclude that the distribution of our residuals does indeed come from a chi-squared distribution.

Lastly, the Breusch Pagan test is one that attempts to find heteroscedasticity in our linear model. This means that we are attempting to see whether or not the residuals our model predicts have too much range. Too much range will result in a conical shaped graphical representation of our residuals whereas a homoscedastic result will result in something more linear. We see from our resulting R statistics that residual standard error is .003711, which implies very low variability in our predicted values, and furthermore, our residuals. In this case, we can reject the null hypothesis that the model is heteroscedastic and accept the alternative hypothesis that it is indeed homoscedastic.

* 1. ***Impose the restriction and re-estimate the model. Report results using stargazer.***

===============================================

Dependent variable:

---------------------------

lnprice

-----------------------------------------------

lnestimate 0.846\*\*\*

(0.028)

Constant 2.095\*\*\*

(0.375)

-----------------------------------------------

Observations 44

R2 0.957

Adjusted R2 0.956

Residual Std. Error 0.054 (df = 42)

F Statistic 927.322\*\*\* (df = 1; 42)

===============================================

Note: \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

* 1. ***Test whether or not the model is a valid restriction of the general model and report the results from this test. Find the residual sum of squares as an object in R.***

RSSu = .107

RSSr = .121

F = [(RSSR-RSSU)/q]/[RSSU/(n-k)]

F = [(.121-.107)/8]/[.107/(44-9)]

F = .56

We can test the model at the 10% significance level, which produces a critical value of 1.852. When we compare our F-statistic to this critical value, we see that it falls far below. What this means is that the null hypothesis can indeed be rejected. That is, the linear model is a proper fit. Given our significance level, we can be 90% certain that our linear regression model on housing prices for this certain website is correctly specified. This means that this website, with a large level of confidence, is correct in the values it predicts for the given houses in the Davis community.

**R Code:**

### Problem 1 ###

production<- read.table("production.csv", header=TRUE, sep=",")

lnY = log(production$Y)

lnK = log(production$K)

lnL = log(production$L)

olsproduction <- lm(lnY ~ lnK + lnL, data=production)

install.packages("stargazer")

library(stargazer)

stargazer(olsproduction, type="text")

lnYL = lnY - lnL

lnKL = lnK - lnL

olsrestrictedproduction <- lm(lnYL ~ lnKL, data=production)

stargazer(olsrestrictedproduction, type="text")

RSSuproduction <- sum(resid(olsproduction)^2)

RSSrproduction <- sum(resid(olsrestrictedproduction)^2)

RSSuproduction

RSSrproduction

Ftest <- ((RSSrproduction-RSSuproduction)/1)/(RSSuproduction/(73-3))

Ftest

qf(.9,1,70)

pvalue <- 1-pf(Ftest, 1, 70)

pvalue

### Problem 2 ###

housing<- read.table("housingprices.csv", header=TRUE, sep=",")

lnestimate<-log(housing$estimate)

lnsqrft<-log(housing$sqrft)

lnlotsize<-log(housing$lotsize)

lnprice<-log(housing$price)

olsu<-lm(lnprice ~ lnestimate + bdrms + bathrms + lnsqrft + lnlotsize + age + pool + central, data=housing)

stargazer(olsu, type="text")

install.packages("lmtest")

install.packages("tseries")

library(lmtest)

library(tseries)

resettest(olsu)

residualsu <- resid(olsu)

jarque.bera.test(residualsu)

residsqu <- resid(olsu)^2

bptestu <- lm(residsqu ~ lnestimate + bdrms + bathrms + lnsqrft + lnlotsize + age + pool + central, data=housing)

summary(bptestu)

olsr <- lm(lnprice ~ lnestimate, data=housing)

stargazer(olsr, type="text")

RSSu <- sum(resid(olsu)^2)

RSSr <- sum(resid(olsr)^2)

RSSu

RSSr

Ftesthousing <- ((RSSr-RSSu)/8)/(RSSu/(44-9))

Ftesthousing

qf(.90,8,35)

pvaluehousing <- 1-pf(Ftesthousing, 8, 35)

pvaluehousing