Study Guide for Final Exam

Chapter Five

1. What is Hypothesis Testing?

A. Formulating the null and alternative hypotheses

  (i) What is the convention we use in formulating the null and alternative hypotheses? Know that the null hypothesis is the statement of what we believe to be untrue whereas the alternative states what we expect to be theoretically true.

  (ii) What are the errors associated with hypothesis testing - know how to define and illustrate (give an example of) Type I and Type II errors.

B. What is a decision rule? How does a decision rule help us determine whether to reject or accept the hypothesis of interest.

2. Normality of the Errors and the Sampling Distributions of $\hat{\beta}_0$ and $\hat{\beta}_1$

A. Be able to define the assumption of normality using words and math.

B. How does the assumption that the errors follow a normal distribution help us find out what the sampling distributions of $\hat{\beta}_0$ and $\hat{\beta}_1$ are?

3. The t-statistic

A. What is the t-statistic? Know how to use the t-statistic to test hypotheses about a single coefficient.
B. How is the t-statistic distributed under the null hypothesis?

4. Review of t-tests – know the uses of the t-test.

A. Testing for significance of an estimated coefficient.

(i) Use one-tailed t-test when the expected sign of the coefficient is either positive or negative.

STEP 1: Case1 - $H_0: \beta = 0$ $H_1: \beta > 0$
Case2 - $H_0: \beta = 0$ $H_1: \beta < 0$

STEP 2: The test statistic is $t = \dfrac{\hat{\beta}}{s_{\hat{\beta}}} \approx t_{n-K-1}$.

STEP 3: Choose a level of significance and obtain the critical value corresponding to (n-K-1) degrees of freedom.

STEP 4: Reject H_0 if $|t| > t_c$.

(ii) Use two-tailed t-test when the expected sign of the coefficient is unknown.

STEP 1: $H_0: \beta = 0$ $H_1: \beta \neq 0$

STEP 2: The test statistic is $t = \dfrac{\hat{\beta}}{s_{\hat{\beta}}} \approx t_{n-K-1}$.

STEP 3: Choose a level of significance and obtain the critical value corresponding to (n-K-1) degrees of freedom.

STEP 4: Reject H_0 if $|t| > t_c$. That is reject H_0 if $t > t_c$ or $-t < -t_c$

B. Two-tailed t-tests of a specific nonzero coefficient value

STEP 1: $H_0: \beta = \beta_{H0}$ $H_1: \beta \neq \beta_{H0}$

STEP 2: The test statistic is $t = \dfrac{\hat{\beta} - \beta_{H0}}{s_{\hat{\beta}}} \approx t_{n-K-1}$.

STEP 3: Choose a level of significance and obtain the critical value corresponding to (n-K-1) degrees of freedom.

STEP 4: Reject H_0 if $|t| > t_c$. That is reject H_0 if $t > t_c$ or $-t < -t_c$. Note: to the extent that we expect the hypothesized value β_{H0} to be correct, we violate the practice of using the null hypothesis to state that which we expect to be untrue.

C. One-tailed t-test for the sign of a particular coefficient

STEP 1: Case1 - $H_0: \beta \geq 0$, $H_1: \beta < 0$
Case2: - $H_0: \beta \leq 0$, $H_1: \beta > 0$

STEP 2: The test statistic is $t = \dfrac{\hat{\beta}}{s_{\hat{\beta}}} \approx t_{n-K-1}$.

STEP 3: Choose a level of significance and obtain the critical value corresponding to (n-K-1) degrees of freedom.

Step 4: Reject H_0 if $|t| > t_c$ and if t has the sign implied under the alternative hypothesis.

D. Testing for correlation between independent variables

STEP 1: Case1 - $H_0: r \geq 0$, $H_1: r < 0$ - no positive correlation
Case2: - $H_0: r \leq 0$, $H_1: r > 0$ - no negative correlation

STEP 2: The test statistic is $t = \dfrac{r\sqrt{n-2}}{\sqrt{(1-r^2)}} \approx t_{n-2}$.

STEP 3: Choose a level of significance and obtain the critical value corresponding to (n-2) degrees of freedom.

Step 4: Reject H_0 if $|t| > t_c$ and if t has the sign implied under the alternative hypothesis.

E. Know the properties and limitations of t-tests

(i) The t-tests for significance, for a specific nonzero value, and for the sign of a coefficient are all centered around zero.

(ii) The sampling distribution of the t-statistic is based on the normality of the error term and on the other Classical assumptions. Intuitively, the sampling distribution of $\hat{\beta}$ is based on the normality of the error term and on the other Classical assumptions. Furthermore, both $\hat{\beta}$ and SE($\hat{\beta}$) have known sampling distributions. If any of the assumptions are violated, the t-statistic will not necessarily follow the t-distribution detailed in table B-1.

(iii) The t-test has several limitations

- The t-test does not test theoretical validity.

- The t-test does not test "importance", i.e. the most statistically significant variable is not always the most "important".

- The t-test is not intended for tests of the entire population.

- A t-test cannot be used to test hypotheses about more than one coefficient at a time. If we wish to test whether two or more coefficients are jointly significant we use the F-test.

5. The F-test: know how to perform a test for overall significance

STEP 1: H_0: $\beta_1 = \beta_2 = ... = \beta_k = 0$, H_1: H_0 is not true.
STEP 2: The test statistic is

$$F = \frac{ESS/K}{RSS/(n-K-1)} = \frac{R^2/K}{(1-R^2)/(n-K-1)} \approx F_{n-K-1}\,.$$

STEP 3: Choose a level of significance. In Table B-2 obtain the critical value $F_{K,(n-K-1)}$ where K = d.f in the numerator and (n-K-1) = d.f in the denominator.
STEP 4: Reject H_0 if $F \geq F_c$. That is reject the null hypothesis that β_1, β_2, ..., β_k are jointly not significantly different from zero.

Extended Outline: Chapter 6

In choosing the independent variables that belong in a model, two types of errors are likely:
(i) the omission of a variable that belongs in the model;
(ii) the inclusion of an irrelevant variable.

***Main questions**: What are the theoretical consequences of each of the two types of specification errors listed above?*

6.1. Know the consequences of omitting a relevant variable.

Suppose the true regression model is:

Eq. (1) $$Y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \varepsilon_i$$

where ε_i is a classical error term (white noise).

Now, suppose we omit X_2 from Equation 1 and so we estimate instead:
Eq. (2) $$Y_i = \beta_0 + \beta_1 X_{1i} + \varepsilon_i^*$$
where ε_i^* represents:
Eq. (3) $$\varepsilon_i^* = \varepsilon_i + \beta_2 X_{2i}$$
The *estimated* regression is:
Eq. (4) $$Y_i = \hat{\beta}_0^* + \hat{\beta}_1^* X_{1i} + e_i$$

1. Question: Besides Assumption 1, what other assumption(s) does equation (2) violate if X_1 is somehow related to X_2?
   Answer: Assumption (3) – All explanatory variables are uncorrelated with the error term.

2. Question: If the estimated regression model violates Assumption (3), what problem do we have?
   Answer: The estimated coefficient is biased, i.e. E($\hat{\beta}_1^*$) ≠ β_1. Thus the OLS estimator of $\hat{\beta}_1$ is no longer BLUE (the Gauss-Markov Theorem does not hold in this case).

Summary: The consequences of misspecification resulting from the omission of an important explanatory variable are listed below:

1. If an independent variable whose true regression coefficient is nonzero is excluded from a model, the estimated values of all the other regression coefficients will be biased unless the excluded variable is uncorrelated with every included variable.
2. Even if the condition in above is met, the estimated constant term is generally biased and hence forecasts will also be biased.
3. The estimated variance of the regression coefficient of an included variable will generally be biased, and hence tests of hypotheses are invalid.

6.2. Know the consequences of inclusion of an irrelevant variable

Suppose the true regression model is:

$$Y_i = \beta_0 + \beta_1 X_{1i} + \varepsilon_i$$

but we erroneously include the variable X_2 so that we estimate the model:

$$Y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \varepsilon_i^*$$

As before the true residual, ε_i, satisfies the classical assumptions. What are the consequences of this kind of misspecification? Is the estimator of β_2 biased? Is it BLUE? Are the tests of Hypotheses valid? The answers to these questions are summarized below.

1. If an independent variable whose true regression coefficient is zero (that is the variable is redundant) is included in the model, the estimated values of all the other regression coefficients will still be unbiased and consistent.

2. Their variance, however, will be higher than that without the irrelevant variable, and hence the coefficients will be inefficient.

3. Because the estimated variances of the regression coefficients are unbiased, tests of hypotheses are still valid.

The consequences of including an irrelevant variable are thus less serious as compared to omitting an important variable.

Extended outline: Chapter 8

I. Introduction

Previously we have stated that the regression coefficient for a particular variable is a measure of its own partial effect, that is, its effect when all other variables in the model are at fixed levels and only its value is changed. When two explanatory variables move closely together, however, we cannot simply hold one constant and change the other because when the latter is changed, so would the former. In this situation it will be difficult to isolate the partial effect of a single variable. This is the problem of ***multicollinearity***, which arises when explanatory variables have approximate linear relationships.

II. Perfect vs. Imperfect Multicollinearity.

1. Know the consequences of perfect multicollinearity.

A/. Perfect Multicollinearity violates classical assumption VI: No explanatory variable is a perfect linear function of any other explanatory variable(s), i.e. no perfect multicollinearity.

B/. The word "perfect" implies that the variation in one explanatory variable can be completely explained by movements in another explanatory variable.

C/. Such a perfect linear function between two independent variables:
Eq. (1) $X_{1i} = \alpha_0 + \alpha_1 X_{2i}$

where the αs are constants and the Xs are independent variables in the following regression:

Eq. (2) $Y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \varepsilon_i$

<u>NOTE</u>: there is no error term in equation (1) which implies the X_1 can be exactly calculated given X_2 and the parameters of the equation (i.e. the αs).

<u>Question</u>: What happens to the OLS estimation of a regression in which some of the explanatory variables are perfectly correlated?

<u>Answer</u>: OLS is incapable of generating estimates of the regression coefficients; $\hat{\beta}_1$ is indeterminate and so is $\hat{\beta}_2$; the standard errors of $\hat{\beta}_1$ and $\hat{\beta}_2$ are undefined, i.e. SE($\hat{\beta}_1$) = ∞ and SE($\hat{\beta}_2$) = ∞. When there is perfect multicollinearity, the regression coefficients cannot be estimated because the perfectly correlated variables are indistinguishable in terms of their effect on the dependent variable.

2. Imperfect Multicollinearity.

In most applications involving economic data two or more explanatory variables are not exactly linearly related but can be approximately so. That is collinearity can be "high" but not perfect. This is the case of near, or imperfect, or high multicollinearity.

III. The theoretical consequences of multicollinearity

Recall that given the assumptions of the CLRM, OLS estimators are best linear unbiased estimators (BLUE). Then why are we worried about multicollinearity? There are several reasons:

1. OLS estimators are unbiased but *unbiasedness is a repeated sampling property*. It says nothing about the properties of the estimates in any one given sample. In reality we rarely have the luxury of repeating samples.

2. Imperfect multicollinearity does not destroy the minimum variance property of OLS estimators. But! *Minimum variance does not mean that the numerical value of the variance will be small*.

3. *Multicollinearity is essentially a sample (regression) phenomenon* -- even if the X variables are not linearly correlated in the population (i.e. PRF), they may be so highly collinear in a sample that we cannot isolate their individual influence on Y.

IV. The practical consequences of multicollinearity

In the cases of near or high multicollinearity, we are likely to encounter one or more of the following problems:

1. *Large variances and standard error of OLS estimators*. As the standard error of an estimator increases, it becomes more difficult to estimate the true value of the estimator (i.e. the true beta). That is, there is a fall in the precision of the OLS estimators.
2. *Wider confidence intervals.* Because of large standard errors, confidence intervals for relevant population parameters tend to be large.
3. *"Insignificant" t-ratios*. In the presence of multicollinearity, the estimated standard errors increase dramatically, thereby making t-values smaller. Therefore, in such cases, one will increase the probability of accepting the null hypothesis that the relevant true population coefficient is zero.
4. *A high R^2 value but few significant t-ratios.*
5. *OLS estimators and their standard errors become very sensitive to small changes in the data.*
6. *Wrong signs for regression coefficients.*
7. *Difficulty in assessing the individual contributions of explanatory variables to the explained sum of squares or R^2.*

V. Detection of multicollinearity

Know and understand how we detect the presence of, and severity, of multicollinearity?

There are several rules of thumb, or indicators, that will provide us with some clue about the existence of multicollinearity in concrete applications. Some of these indicators follow.

1. *High R^2 but few significant t ratios.* This is the "classical" symptom of multicollinearity. If the R^2 is high, in excess of 0.8, the *F*-test in most cases will reject the null hypothesis that the partial slope coefficients are jointly (or simultaneously) equal to zero. But individual *t*-tests will show that none, or very few, partial slope coefficients are statistically different from zero.

2. *High pair-wise correlations among explanatory variables*. Recall that we can compute the correlation coefficient between two explanatory variables, X_1 and X_2, using the formula:

$$r_{12} = \frac{\sum_{i=1}^{n}\left[(X_{1i} - \overline{X}_1)(X_{2i} - \overline{X}_2)\right]}{\sqrt{\sum_{i=1}^{n}(X_{1i} - \overline{X}_1)^2 \sum_{i=1}^{n}(X_{2i} - \overline{X}_2)^2}}$$

3. *Auxiliary regressions*. Since multicollinearity arises because one or more of the explanatory variables are exact or near exact linear combinations of other explanatory variables, one way of finding out which explanatory variable (or X variable) is highly collinear with the other explanatory variables in the model is to regress each X variable on the remaining X variables and to compute the corresponding R^2.

4. The Variance Inflation Factor (VIF). The R^2 values obtained from the various auxiliary regressions may <u>not</u> be totally reliable diagnostics of multicollinearity. Since one of our main concerns is the high variance of OLS estimators in the presence of high multicollinearity, we can compute a measure of

how much multicollinearity has increased the variance of an estimated coefficient. This measure is called the *variance inflation factor* (VIF):

$$VIF = \frac{1}{1-R_i^2}$$

The higher a variable's VIF, the higher the variance of the estimated coefficient.

Warning: A low VIF does not necessarily mean that there is no multicollinearity between variables. It is a sufficient but not necessary test for multicollinearity just like all the other tests before it. Given the research (in the field of Econometrics) so far, we still do not have a test that can definitively rule out or confirm the presence of high multicollinearity.

VI. What to do with Multicollinearity?

1. Do Nothing
2. Drop a redundant variable
3. Transform the multicollinear variables
4. Increase the size of the sample.

Serial Correlation (Chapter 9)

I. Nature of Autocorrelation

(i) Be able to define serial independence of the error terms and explain what the consequences of serial correlation are.
(ii) Be able to explain the difference between pure and impure serial correlation.
(iii) Be able to explain how specification errors can lead to serial dependence of the error terms.

Specifically know the following cases:

A/. Omitted Variables. Serial correlation may be the product of the exclusion of an important explanatory variable. That is, suppose you estimate the model:

$$Y_t = \beta_0 + \beta_1 X_{t1} + \varepsilon_t$$

but the true data generating process is

$$Y_t = \beta_0 + \beta_1 X_{t1} + \beta_2 X_{t2} + u_t$$

Therefore, the error term in your estimated model will be equal to:

$$\varepsilon_t = \beta_2 X_{t2} + u_t$$

That is, the effect of the omitted variable will be captured by the error term ε_t. Another case of omitted variables arises when the researcher ignores important lagged effects.

B/. Incorrect functional form. Serial correlation can also be caused by misspecification of the functional form. For example, suppose you estimate the following model:

$$Y_t = \beta_0 + \beta_1 X_t + \varepsilon_t$$

but the true data generating process is:

$$Y_t = \beta_0 + \beta_1 X_t + \beta_2 X_t^2 + u_t$$

Therefore, the error term in your estimated model will reflect a systematic patter which can be expressed as:

$$\varepsilon_t = \beta_2 X^2_{t1} + u_t$$

Thus, is the relationship between Y and X is quadratic but we assume a straight line, then the error term ε_t will depend on X^2, once again creating "false" or impure autocorrelation.

C/. Data Manipulation and systematic errors in measurement can also cause autocorrelation.
NOTE: The problem of autocorrelation is usually more common in time series data – *be able to explain why.*

II. What are the theoretical and practical consequences of autocorrelation?

1. Serial Correlation of the First Order (Know the difference between positive and negative autocorrelation).

First-order serial correlation: If serial correlation is present, then Cov(ε_t, ε_s) ≠ 0 for t ≠ s; that is, the error for period t is correlated with the error for period s. Specify the regression model with serial correlated error as:

Eq. (1) $$Y_t = \beta_0 + \beta_1 X_t + \varepsilon_t$$

where ε_i follows a first order auto regressive process, AR(1) process, described mathematically as follows:

Eq. (2) $$\varepsilon_t = \rho\varepsilon_{t-1} + u_t$$

The error term ε_t is thus related to the previous period's error ε_{t-1}, a new error term u_t and a new parameter ρ (rho). Because ρ is the coefficient of the error term lagged one period it is called ***the first-order autocorrelation coefficient*** and takes on values in the range $-1 < \rho < 1$ and u_t is assumed to be a white noise, zero mean classical error term.

2. Consequences of Ignoring Serial Correlation

Know and understand the consequences of ignoring serial correlation?

If we ignore the serial correlation in error, the impacts on the OLS estimates are as follows:

- OLS estimates (and forecasts based on them) are unbiased and consistent even if the error terms are serially correlated.
- But least square estimators are not efficient (i.e. OLS estimates are not BLUE and do not have the minimum variance property).
- The estimated variances of OLS estimators are biased. Therefore, the usual *t*-tests and *F*-tests are not generally reliable.
- The usual formula to compute the error variance, namely, $\hat{\sigma}^2 = \frac{RSS}{d.f.}$, is a biased estimator of the true σ^2 and in some cases it is likely to underestimate the latter.
- As a consequence the computed R^2 may be an unreliable measure of true R^2**.**
- The conventionally computed variances and standard errors of forecast may also be inefficient.

III. Detection of Autocorrelation

1. **The residual plot (a.k.a. time-sequence plot).** If successive residuals tend to cluster on one side of the zero line or the other, this is a graphical indication of the presence of serial correlation.

2. **The Durbin-Watson *d* test. The Durbin-Watson *d*-statistic is defined as:**

$$d = \frac{\sum_{t=2}^{n}(e_t - e_{t-1})^2}{\sum_{t=1}^{n} e_t^2}$$

It can be shown that for large sample sizes, the d-statistic can be *approximately* expressed as:***d ≈ 2(1- $\hat{\rho}$)***
where $\hat{\rho}$ is an estimator of the coefficient of autocorrelation ρ of the AR(1) scheme $\varepsilon_t = \rho\varepsilon_{t-1} + u_t$.
But since $-1 \le \rho \le 1$, the relationship *d ≈ 2(1- $\hat{\rho}$)* implies the following:

Value of ρ	Value of d (approximately)
$\rho = -1$ (perfect negative autocorrelation)	$d = 4$
$\rho = 0$ (no autocorrelation)	$d = 2$
$\rho = 1$ (perfect positive autocorrelation)	$d = 0$

In summary, $0 \le d \le 4$, that is the computed d value must lie between 0 and 4. For the above table we can state that:
- if the computed d value is closer to 0, there is evidence of positive autocorrelation;
- if the computed d value is closer to 4, there is evidence of negative autocorrelation;
- the closer the computed d value is to 2, the more the evidence in favor of no autocorrelation.

3. **Know how to conduct a Durbin Watson d-test for autocorrelation.**

In a multiple regression model, $Y_t = \beta_0 + \beta_1 X_{t1} + \beta_2 X_{t2} + \ldots + \beta_k X_{tk} + \varepsilon_t$, and $\varepsilon_t = \rho\varepsilon_{t-1} + u_t$, *the* Durbin-Watson statistic is used to rest for autocorrelation as follows:

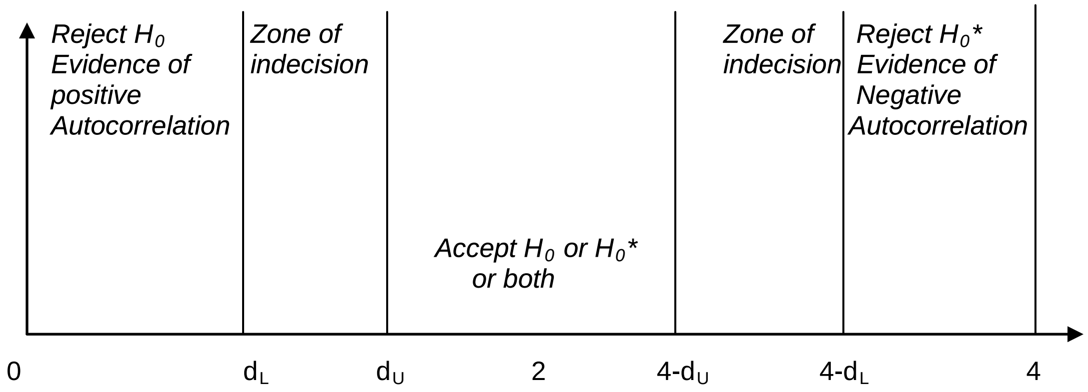
Step 1: Estimate the model with OLS and obtain the residuals e_t.

Step 2: Compute the Durbin-Watson *d* statistic: $$d = \frac{\sum_{t=2}^{n}(e_t - e_{t-1})^2}{\sum_{t=1}^{n} e_t^2}$$

Step 3: Find out the critical d_L and d_U from the Durbin Watson tables for the given sample size and the given number of explanatory variables.
Step 4: Follow the decision rules in the table below for the various null hypotheses:

Null Hypothesis	**Decision Rule**	**If**
H_0: No Positive autocorrelation ($\rho \le 0$)	Reject	$0 < d < d_L$
H_0: No Positive autocorrelation ($\rho \le 0$)	No Decision	$d_L \le d \le d_U$
H_0^*: No Negative autocorrelation ($\rho \ge 0$)	Reject	$4 - d_L < d < 4$
H_0^*: No Negative autocorrelation ($\rho \ge 0$)	No Decision	$4 - d_U \le d \le 4 - d_L$
H_0 or H_0^* (or both): No Positive or negative autocorrelation ($\rho = 0$)	Do not Reject	$d_U < d < 4 - d_U$

The figure below depicts these rules graphically.



IV. What are the remedies for the problem of autocorrelation?

Understand how GLS works!

1. Serial Correlation in Time Series Data

A/. Serial correlation in time series data when the structure of serial correlation is known

In practice, the structure of serial correlation is usually assumed to be an AR(1), that is $\varepsilon_t = \rho\varepsilon_{t-1} + u_t$ *where the* u_t*s satisfy the usual OLS assumptions and* ρ **is KNOWN**.

Recall the two-variable regression model: $Y_t = \beta_0 + \beta_1 X_t + \varepsilon_t$ *where* $\varepsilon_t = \rho\varepsilon_{t-1} + u_t$ *and* u_t *is a random white noise error term.* We can transform this model so that the error term is serially independent. First, rewrite the two variable regression with a one-period lag:

$$Y_{t-1} = \beta_0 + \beta_1 X_{t-1} + \varepsilon_{t-1}$$

Multiply the regression on both sides by ρ on both sides to obtain

$$\rho Y_{t-1} = \rho\beta_0 + \rho\beta_1 X_{t-1} + \rho\varepsilon_{t-1}$$

now subtract this equation from the original to yield:

$$(Y_t - \rho Y_{t-1}) = \beta_0(1-\rho) + \beta_1(X_t - \rho X_{t-1}) + (\varepsilon_t - \rho\varepsilon_{t-1})$$

Using the AR(1) process where $\varepsilon_t = \rho\varepsilon_{t-1} + u_t$ *or* $u_t = \varepsilon_t - \rho\varepsilon_{t-1}$ *we can rewrite the above equation as:*

$$(Y_t - \rho Y_{t-1}) = \beta_0(1-\rho) + \beta_1(X_t - \rho X_{t-1}) + u_t$$

The above transformation provides us with a model free from serial correlation which we can rewrite as:

$$Y_t^* = \beta_0^* + \beta_1 X_t^* + u_t$$

where $Y_t^* = (Y_t - \rho Y_{t-1})$; $\beta_0^* = \beta_0(1-\rho)$; $X_t^* = (X_t - \rho X_{t-1})$. If we apply OLS to the transformed variables Y* and X*, the estimators thus obtained will have the desirable BLUE property. These estimators are called *Generalized Least Squares (GLS) estimators* and the above equation is known as the *generalized difference equation*. While the GLS model seems to offer a solution to autocorrelation, it also has a problem: *it assumes that* ρ *is known.* Of course, we do not know ρ so to be able to use the GLS model we must find ways to estimate the **unknown ρ**.

B/. Serial correlation in Time series data when the structure of serial correlation is unknown

In practice, the structure of serial correlation is rarely, if ever, known. In this case, then, it should be evident that what one needs to do is obtain an estimate of ρ.

(i) ρ estimated from the Durbin Watson Statistic

Recall earlier that we established the following approximate relationship between the *d* statistic and ρ:

$d \approx 2(1-\hat{\rho})$, from which we obtain $\hat{\rho} \approx 1 - \frac{d}{2}$.

Caveat: Although easy to use, this method of transformation generally gives good estimates of ρ if the sample size is large.

(ii) The Cochrane-Orcutt two-step iterative procedure.

To illustrate this procedure we will continue to use our two-variable regression model and begin by assuming first an AR(1) process for the population errors. Recall our transformed GLS equation:

$$(Y_t - \rho Y_{t-1}) = \beta_0(1-\rho) + \beta_1(X_t - \rho X_{t-1}) + u_t$$

for which we needed an estimate of ρ. To obtain an estimate of ρ with which we can proceed to estimate the GLS equation we follow these two steps:

Step 1: Estimate ρ by running a regression using the residuals of the equation suspected of having serial correlation: $e_t = \hat{\rho} e_{t-1} + u_t$ where the e_ts are the OLS residuals from the equation suspected of having pure serial correlation and u_t is a well-behaved error term.

Step 2: Use the value of $\hat{\rho}$ *to estimate the GLS equation above by substituting* $\hat{\rho}$ *and using OLS to estimate the equation with the adjusted data:*

$$(Y_t - \hat{\rho} Y_{t-1}) = \beta_0(1- \hat{\rho}) + \beta_1(X_t - \hat{\rho} X_{t-1}) + u_t$$

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Final Exam: Wednesday, June 8th, 2011 (10:15 am - 12:05 pm).

Format*: Four questions that resemble end-of-chapter exercises.*

General: The final exam is closed-book, closed-notes exam. Your copy of the exam will be complemented with blank sheets where you can provide your answers. You may bring a *simple (non-programmable)* calculator. If you do not have such a calculator, I will be happy to loan you one.

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