EXHIBIT K

OMNIBUS BROWN DECLARATION

A Guide to Modern Econometrics

2nd edition

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is a specific value chosen by the researcher. If this hypothesis is true we know that the statistic

$$t_k = \frac{b_k - \beta_k^0}{\text{se}(b_k)} \tag{2.49}$$

has a t distribution with $N - K$ degrees of freedom. If the null hypothesis is not true, the alternative hypothesis H_1: $\beta_k \neq \beta_k^0$ holds. As there are no unknown values in t_k, it becomes a **test statistic** that can be computed from the estimate b_k and its standard error se(b_k). The usual testing strategy is to reject the null hypothesis if t_k realizes a value that is very unlikely if the null hypothesis is true. In this case this means very large absolute values for t_k. To be precise, one rejects the null hypothesis if the probability of observing a value of $|t_k|$ or larger is smaller than a given **significance level** α, often 5%. From this, one can define the **critical values** $t_{N-K;\alpha/2}$ using

$$P\{|t_k| > t_{N-K;\alpha/2}\} = \alpha.$$

For $N - K$ not too small, these critical values are only slightly larger than those of the standard normal distribution, for which the two-tailed critical value for $\alpha = 0.05$ is 1.96. Consequently, at the 5% level the null hypothesis will be rejected if

$$|t_k| > 1.96.$$

The above test is referred to as a **two-sided test** because the alternative hypothesis allows for values of β_k on both sides of β_k^0. Occasionally, the alternative hypothesis is one-sided, for example: the expected wage for a man is larger than that for a woman. Formally, we define the null hypothesis as H_0: $\beta_k \leq \beta_k^0$ with alternative H_1: $\beta_k > \beta_k^0$. Next we consider the distribution of the test statistic t_k at the boundary of the null hypothesis (i.e. under $\beta_k = \beta_k^0$, as before) and we reject the null hypothesis if t_k is too large (note that large values for b_k lead to large values for t_k). Large negative values for t_k are compatible with the null hypothesis and do not lead to its rejection. Thus for this **one-sided test**, the critical value is determined from

$$P\{t_k > t_{N-K;\alpha}\} = \alpha.$$

Using the standard normal approximation again, we reject the null hypothesis at the 5% level if

$$t_k > 1.64.$$

Regression packages typically report the following t-value,

$$t_k = \frac{b_k}{\text{se}(b_k)},$$

sometimes referred to as the t-ratio, which is the point estimate divided by its standard error. The t-ratio is the t-statistic one would compute to test the null hypothesis that $\beta_k = 0$, which may be a hypothesis that is of economic interest as well. If it is rejected, it is said that 'b_k differs significantly from zero', or that the corresponding variable

2.5.7 Size, Power and p-Values

When an hypothesis is statistically tested two types of errors can be made. The first one is that we reject the null hypothesis while it is actually true, and is referred to as a **type I error**. The second one, a **type II error**, is that the null hypothesis is not rejected while the alternative is true. The probability of a type I error is directly controlled by the researcher through his choice of the significance level α. When a test is performed at the 5% level, the probability of rejecting the null hypothesis while it is true is 5%. This probability (significance level) is often referred to as the **size** of the test. The probability of a type II error depends upon the true parameter values. Intuitively, if the truth deviates much from the stated null hypothesis, the probability of such an error will be relatively small, while it will be quite large if the null hypothesis is close to the truth. The reverse probability, that is, the probability of rejecting the null hypothesis when it is false, is known as the **power** of the test. It indicates how 'powerful' a test is in finding deviations from the null hypothesis (depending upon the true parameter value). In general, reducing the size of a test will decrease its power, so that there is a trade-off between type I and type II errors.

Suppose that we are testing the hypothesis that $\beta_2 = 0$, while its true value is in fact 0.1. It is clear that the probability that we reject the null hypothesis depends upon the standard error of our OLS estimator b_2 and thus, among other things, upon the sample size. The larger the sample the smaller the standard error and the more likely we are to reject. This implies that type II errors become increasingly unlikely if we have large samples. To compensate for this, researchers typically reduce the probability of type I errors (that is of incorrectly rejecting the null hypothesis) by lowering the size α of their tests. This explains why in large samples it is more appropriate to choose a size of 1% or less rather than the 'traditional' 5%. Similarly, in very small samples we may prefer to work with a significance level of 10%.

Commonly, the null hypothesis that is chosen is assumed to be true unless there is convincing evidence of the contrary. This suggests that if a test does not reject, for whatever reason, we stick to the null hypothesis. This view is not completely appropriate. A range of alternative hypotheses could be tested (for example $\beta_2 = 0$, $\beta_2 = 0.1$ and $\beta_2 = 0.5$), with the result that none of them is rejected. Obviously, concluding that these three null hypotheses are simultaneously true would be ridiculous. The only appropriate conclusion is that we *cannot reject* that β_2 is 0, nor that it is 0.1 or 0.5. Sometimes, econometric tests are simply not very powerful and very large sample sizes are needed to reject a given hypothesis.

A final probability that plays a role in statistical tests is usually referred to as the ***p*-value**. This p or probability value denotes the minimum size for which the null hypothesis would still be rejected. It is defined as the probability, under the null, to find a test statistic that (in absolute value) exceeds the value of the statistic that is computed from the sample. If the p-value is smaller than the significance level α, the null hypothesis is rejected. Many modern software packages supply such p-values and in this way allow researchers to draw their conclusions without consulting or computing the appropriate critical values. It also shows the sensitivity of the decision to reject the null hypothesis, with respect to the choice of significance level. For example, a p-value of 0.08 indicates that the null hypothesis is rejected at the 10% significance level, but not at the 5% level.