EXHIBIT F

ECONOMETRIC MODELS AND ECONOMIC FORECASTS

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Type II error. The choice to be made depends on the particular problem, but in econometrics it is usual to choose a rather low level of significance and a low probability of Type I error.

2.5.2 p-Values

Most statistical analyses report tests of statistical significance by pointing out which coefficients are significant at the 1 percent, 5 percent, or other appropriate significance level. However, it is sometimes useful to provide additional information in the form of a *p-value (probability value).* A p-value describes the exact significance level associated with a particular econometric result. Thus, a p-value of .07 indicates that a coefficient is statistically significant at the .07 level (but not at the 5 percent level). In the context of a two-tailed test using a normal distribution, this means that 7 percent of the t distribution lies outside the interval plus or minus 1.96 standard deviations from the mean.

Typically the null hypothesis being tested will be the hypothesis that a particular regression coefficient is equal to 0. The p-value therefore is the probability of getting data that generate a coefficient estimate as large as or larger than the estimated coefficient, given that the null hypothesis of a zero coefficient is true. The smaller the p-value for a given study, the more surprising it will be to see such a result if the null hypothesis is valid. Correspondingly, a large p-value indicates that the data are consistent with the null hypothesis.

The p-value measures the likelihood of a Type I error (as discussed in Section 2.5.1), the probability of incorrectly rejecting a correct null hypothesis. The higher the p-value, the more likely it is that we will err in rejecting the null hypothesis; the lower the p-value, the more comfortable we can feel in rejecting it.

2.5.3 The Power of a Test

A high p-value signifies that a coefficient is not significantly different from zero; as a result the researcher fails to reject the null hypothesis that the coefficient is zero. What are the reasons for this "failure"? One obvious reason could be that the null hypothesis is true. However, an alternative possibility is that the null hypothesis is false but the particular data set used for the test happens to be consistent with the null. (A third possibility—that the model is invalid—will be discussed later in the book.) The statistical concept that helps us evaluate the importance of the second explanation is the *power* of the test. *Power is the probability of rejecting the null hypothesis when it is in fact false.* For any particular null hypothesis, the power is therefore given by 1 minus the probability there will be a Type II error, i.e., 1 minus the probability that one will accept the null hypothesis as true when it is in fact false.

Power depends not only on the size of the effect that has been measured, but also on the size of the data set being studied. Other things being the same, the larger the effect and the larger the sample, the more powerful the test.