Serial correlation is not the only complication that one is likely to encounter when trying to compute unit root test statistics. One very serious problem is that these statistics are severely biased against rejecting the null hypothesis when they are used with data that have been seasonally adjusted by means of a linear filter or by the methods used by government statistical agencies. In Section 19.6, we discussed the tendency of the OLS estimate of α in the regression $y_t = \beta_0 + \alpha y_{t-1} + u_t$ to be biased toward 1 when y_t is a seasonally adjusted series. This bias is present for all the test regressions we have discussed. Even when $\hat{\alpha}$ is not actually biased *toward* 1, it will be less biased *away* from 1 than the corresponding estimate using an unfiltered series. Since the tabulated distributions of the test statistics are based on the behavior of $\hat{\alpha}$ for the latter case, it is likely that test statistics computed using seasonally adjusted data will reject the null hypothesis substantially less often than they should according to the critical values in Table 20.1. That is exactly what Ghysels and Perron (1993) found in a series of Monte Carlo experiments.

If possible, one should therefore avoid using seasonally adjusted data to compute unit root tests. One possibility is to use annual data. This may cause the sample size to be quite small, but the consequences of that are not as severe as one might fear. As Shiller and Perron (1985) point out, the power of these tests depends more on the **span** of the data (i.e., the number of years the sample covers) than on the number of observations. The reason for this is that if α is in fact positive but less than 1, it will be closer to 1 when the data are observed more frequently. Thus a test based on n annual observations may have only slightly less power than a test based on $4n$ quarterly observations that have not been seasonally adjusted and may have more power than a test based on $4n$ seasonally adjusted observations.

If quarterly or monthly data are to be used, they should if possible not be seasonally adjusted. Unfortunately, as we remarked in Chapter 19, seasonally unadjusted data for many time series are not available in many countries. Moreover, the use of seasonally unadjusted data may make it necessary to add seasonal dummy variables to the regression and to account for fourth-order or twelfth-order serial correlation.

A second major problem with unit root tests is that they are very sensitive to the assumption that the process generating the data has been stable over the entire sample period. Perron (1989) showed that the power of unit root tests is dramatically reduced if the level or the trend of a series has changed exogenously at any time during the sample period. Even though the series may actually be stationary in each of the two parts of the sample, it can be almost impossible to reject the null that it is $I(1)$ in such cases.

Perron therefore proposed techniques that can be used to test for unit roots conditional on exogenous changes in level or trend. His tests are performed by first regressing y_t on a constant, a time trend, and one or two dummy variables that allow either the constant, the trend, or both the con-