**Chapter 6 Summary**

In this chapter we covered in some depth the topic of autocorrelation. Time series data are often plagued by autocorrelation. First we discussed the nature and consequences of autocorrelation, then we discussed the methods of detecting autocorrelation, and then we considered ways in which the problem of autocorrelation can be resolved.

Since we generally do not know the true error terms in a regression model, in practice we have to infer the nature of autocorrelation in a concrete application by examining the residuals, which are good proxies for the true error term if the sample size is reasonably large. We can plot the residuals, or use the Durbin–Watson or Breusch–Godfrey (BG) tests.

If the tests of autocorrelation suggest that autocorrelation exists in a given case, we can transform the original model so that in the transformed model we do not face autocorrelation. This is easier said than done, for we do not know the true structure of autocorrelation in the population from which the sample was drawn. We therefore try several transformations, such as the first-difference and generalized difference transformations. Very often this is a trial and error process.

If the sample size is reasonably large, we can use the robust standard errors or HAC standard errors, which do not require any special knowledge of the nature of autocorrelation. The HAC procedure simply modifies the OLS standard errors, without changing the values of the regression coefficients.

Since the OLS estimators are consistent despite autocorrelation, the thrust of the corrective methods discussed in this chapter is to estimate the standard errors of the regression coefficients as efficiently as possible so that we do not draw misleading conclusions about the statistical significance of one or more regression coefficients.