EXHIBIT 16

Econometrics

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There is, however, one problem: Correlated error shocks violate the assumptions of the Gauss-Markov theorem. Specifically, they violate assumption A4, which explicitly assumes that error terms are uncorrelated with one another. In the presence of correlated error terms, ordinary least squares (OLS) is no longer the best linear unbiased estimator (BLUE). We need to adjust our method of estimating the parameters of our model to account for the presence of the correlation in the error terms. Doing so, we can find estimators that are better (more efficient) than the OLS estimator is when the data contains serial correlation. This chapter presents the econometric techniques that handle the case of serially correlated shocks and then shows how they are applied to some simple macroeconomic problems.

12.2 CONSEQUENCES OF AUTOCORRELATION

Suppose that we have a data set that has serial correlation, but we do not realize that we have it and we use OLS to estimate the parameters. What are the consequences for the resulting estimates?

Theorem 12.1 If all the assumptions of the Gauss-Markov theorem are true except A4, and the errors are serially correlated, then:

1. The OLS estimates ($\hat{\beta}$) of the true values of the β parameters remain unbiased;
2. OLS estimates of β parameters remain consistent;
3. OLS estimates of the β parameters become inefficient; there exist other estimators that are unbiased and have smaller variances;
4. The usual standard errors of the OLS estimates become biased and inconsistent.

Intuitively, this happens because, although the error terms are serially correlated, their average value is still 0. They are still equally likely to lie above or below the true regression line; therefore, an estimated line through the center of the data will still tend to lie close to the true line. With enough data, it can be made to lie as close to the true line as desired. However, because the errors tend to come in patterns, and OLS assumes they do not, it is possible to estimate the model more efficiently by accounting for this tendency of the errors to come in patterns, and not distorting the estimated slope and intercept of the line to try to eliminate those patterns.

If all we need to do is estimate the slope and intercept of the relationship, serial correlation does not present a very serious problem. The estimates we get still give us the right answer on average, and they get more reliable as we get more data. They are not the best possible estimates we could get with the data, and it would be nice to do better if we can, but the OLS estimates still work fairly well. The problem comes if we need to know how reliable our estimates are; for example, if we wish to test hypotheses about their true values. Because our standard errors are biased, we do not have reliable information about how far off our estimates of the true βs are likely to be. Worse, the standard errors are biased downward, meaning that the standard errors we calculate are lower than the actual standard errors. In the presence of serial correlation, OLS claims to be more accurate than it really is. This can lead to incorrect hypothesis test results, which will tend to find that parameters are more precisely estimated than they in fact are, and will tend to find that parameters are significantly different from 0 when they are not. Although it is possible to find alternate formulas for the standard errors of the OLS estimates when there is serial correlation, it is typically better to try to fix the problem than to proceed with inefficient estimates.