BOSTON COLLEGE
Department of Economics
EC 228 01 Econometric Methods
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Problem Set 7
Due at classtime, Thursday 4 Dec 2008

Problem sets should be your own work. You may work together with classmates, but if you're not figuring this out on your own, you will eventually regret it.

1. (**C12.6**)

(i) The regression $\hat{u}_t$ on $\hat{u}_{t-1}$ (with 35 observations) gives $\hat{\rho} \approx -.089$ and $se(\hat{\rho}) \approx .178$; there is no evidence of AR(1) serial correlation in this equation, even though it is a static model in the growth rates.

(ii) We regress gc_t on gc_{t-1} and obtain the residuals $\hat{u}_t$. Then, we regress $\hat{u}_t^2$ on gc_{t-1} and gc_{t-1}^2 (using 35 observations), the F-statistic (with 2 and 32 *df*) is about 1.08. The p-value is about .352, and so there is little evidence of heteroskedasticity in the AR(1) model for gc_t. This means that we need not modify our test of the PIH by correcting somehow for heteroskedasticity.

2. (**C12.8**)

(i) This is the model that was estimated in part (vi) of Computer Exercise C10.11. After getting the OLS residuals, $\hat{u}_t$, we run the regression $\hat{u}_t$ on $\hat{u}_{t-1}$, $t = 2, \ldots, 108$. (Included an intercept, but that is unimportant.) The coefficient on $\hat{u}_{t-1}$ is $\rho = .281$ (se = .094). Thus, there is evidence of some positive serial correlation in the errors ($t \approx 2.99$). I strong case can be made that all explanatory variables are strictly exogenous. Certainly there is no concern about the time trend, the seasonal dummy variables, or $wkends$, as these are determined by the calendar. It is seems safe to assume that unexplained changes in $prcfat$ today do not cause future changes in the state-wide unemployment rate. Also, over this period, the policy changes were permanent once they occurred, so strict exogeneity seems reasonable for $spdlaw$ and $beltlaw$. (Given legislative lags, it seems unlikely that the dates the policies went into effect had anything to do with recent, unexplained changes in $prcfat$.

(ii) Remember, we are still estimating the β_j by OLS, but we are computing different standard errors that have some robustness to serial correlation. Using Stata 7.0, I get $\hat{\beta}_{spdlaw} = .0671$, $se(\hat{\beta}_{spdlaw}) = .0267$ and $\hat{\beta}_{beltlaw} = -.0295$, $se(\hat{\beta}_{beltlaw}) = .0331$. The t-statistic for spdlaw has fallen to about 2.5, but it is still significant. Now, the t-statistic on *beltlaw* is less than one in absolute value, so there is little evidence that *beltlaw* had an effect on $prcfat$.

(iii) For brevity, I do not report the time trend and monthly dummies. The final estimate of ρ is $\hat{\rho} = .289$:

$$\begin{array}{rcccccc} \widehat{prcfat} = & \underset{(.102)}{1.009} & + \ldots + & \underset{(.00500)}{.00062} & wkends - & \underset{(.0055)}{.0132} & unem \\ & & + & \underset{(.0268)}{.0641} & spdlaw - & \underset{(.0301)}{.0248} & beltlaw \end{array}$$

$$n = 108, R^2 = .641.$$

There are no drastic changes. Both policy variable coefficients get closer to zero, and the standard errors are bigger than the incorrect OLS standard errors [and, coincidentally, pretty close to the Newey-West standard errors for OLS from part (ii)]. So the basic conclusion is the same: the increase in the speed limit appeared to increase $prcfat$, but the seat belt law, while it is estimated to decrease $prcfat$, does not have a statistically significant effect.

3. (15.4)

(i) The state may set the level of its minimum wage at least partly based on past or expected current economic activity, and this could certainly be part of u_t. Then $gMIN_t$ and u_t are correlated, which causes OLS to be biased and inconsistent.

(ii) Because $gGDP_t$ controls for the overall performance of the U.S. economy, it seems reasonable that $gUSMIN_t$ is uncorrelated with the disturbances to employment growth for a particular state.

(iii) In some years, the U.S. minimum wage will increase in such a way so that it exceeds the state minimum wage, and then the state minimum wage will also increase. Even if the U.S. minimum wage is never binding, it may be that the state increases its minimum wage in response to an increase in the U.S. minimum. If the state minimum is always the U.S. minimum, then $gMIN_t$ is exogenous in this equation and we would just use OLS.

4. (**15.6**)

(i) Plugging (15.26) into (15.22) and rearranging gives

$$y_1 = \beta_0 + \beta_1(\pi_0 + \pi_1 z_1 + \pi_2 z_2 + v_2) + \beta_2 z_1 + u_1$$
$$y_1 = (\beta_0 + \beta_1\pi_0) + (\beta_1\pi_1 + \beta_2)z_1 + \beta_1\pi_2 z_2 + u_1 + \beta_1 v_2$$

and so

$$\alpha_0 = \beta_0 + \beta_1\pi_0$$
$$\alpha_1 = \beta_2 + \beta_1\pi_1$$
$$\alpha_2 = \beta_1\pi_2$$

(ii) From equation in part (i),

$$v_1 = u_1 + \beta_1 v_2$$

(iii) By assumption, u_1 has zero mean and is uncorrelated with z_1 and z_2, and v_2 has these properties by definition. So v_1 has zero mean and is uncorrelated with z_1 and z_2, which means that OLS consistently estimates the α_j. (OLS would only be unbiased if we add the stronger assumptions $E(u_1|z_1, z_2) = E(v_2|z_1, z_2) = 0$.)

5. (**C15.6**)

(i) Sixteen states executed at least one prisoner in 1991, 1992, or 1993. (That is, for 1993, exec is greater than zero for 16 observations.) Texas had by far the most executions with 34.

(ii) The results of the pooled OLS regression are

$$\widehat{mrdrte} = \underset{(4.43)}{-5.28} - \underset{(2.14)}{2.07}\ d93 + \underset{(.263)}{.128}\ exec + \underset{(.78)}{2.53}\ unem$$

$$n = 102, R^2 = .102, \bar{R}^2 = .074.$$

The positive coefficient on *exec* is no evidence of a deterrent effect. Statistically, the coefficient is not different from zero. The coefficient on *unem* implies that higher unemployment rates are associated with higher murder rates.

(iii) When we difference (and use only the changes from 1990 to 1993), we obtain

$$\Delta \widehat{mrdrte} = \underset{(.209)}{.413} - \underset{(.043)}{.104}\ \Delta exec - \underset{(.159)}{.067}\ \Delta unem$$

$$n = 51, R^2 = .110, \bar{R}^2 = .073.$$

The coefficient on $\Delta exec$ is negative and statistically significant (*p*-value $\approx$ .02 against a two-sided alternative), suggesting a deterrent effect. One more execution reduces the murder rate by about .1, so 10 more executions reduce the murder rate by one (which means one murder per 100,000 people). The unemployment rate variable is no longer significant.

(iv) The regression $\Delta exec$ on $\Delta exec_{-1}$ yields

$$\Delta \widehat{exec} = \underset{(.370)}{.350} - \underset{(.17)}{1.08}\ \Delta exec_{-1}$$

$$n = 51, R^2 = .456, \bar{R}^2 = .444.$$

which shows a strong negative correlation in the change in executions. This means that, apparently, states follow policies whereby if executions were high in the preceding three-year period, they are lower, one-for-one, in the next three-year period.

Technically, to test the identification condition, we should add $\Delta unem$ to the regression. But its coefficient is small and statistically very insignificant, and adding it does not change the outcome at all.

(v) When the differenced equation is estimated using $\Delta exec_{-1}$ as an IV for $\Delta exec$,we obtain

$$\Delta \widehat{mrdrte} = \underset{(.211)}{.411} - \underset{(.064)}{.100}\ \Delta exec - \underset{(.159)}{.067}\ \Delta unem$$

$$n = 51, R^2 = .110, \bar{R}^2 = .073.$$

This is very similar to when we estimate the differenced equation by OLS. Not surprisingly, the most important change is that the standard error on $\hat{\beta}_1$ is now larger and reduces the statistically significance of $\hat{\beta}_1$.

6. (**16.5**)

(i) Other things equal, a higher rate of condom usage should reduce the rate of sexually transmitted diseases (STDs). So $\beta_1 < 0$.

(ii) If students having sex behave rationally, and condom usage does prevent STDs, then condom usage should increase as the rate of infection increases.

(iii) If we plug the structural equation for *infrate* into $conuse = \gamma_0 + \gamma_1 infrate + ...$, we see that *conuse* depends on $\gamma_1 u_1$. Because $\gamma_1 > 0$, *conuse* is positively related to u_1. In fact, if the structural error (u_2) in the *conuse* equation is uncorrelated with u_1, $Cov(conuse, u_1) = \gamma_1 Var(u_1) > 0$. If we ignore the other explanatory variables in the *infrate* equation, we can use equation (5.4) to obtain the direction of bias: $plim(\hat{\beta}_1) - \beta_1 > 0$ because $Cov(conuse, u_1) > 0$, where $\hat{\beta}_1$ denotes the OLS estimator. Since we think $\beta_1 < 0$, OLS is biased towards zero. In other words, if we use OLS on the *infrate* equation, we are likely to underestimate the importance of condom use in reducing STDs. (Remember, the more negative is β_1, the more effective is condom usage.)

(iv) We would have to assume that *condis* does not appear, in addition to *conuse*, in the *infrate* equation. This seems reasonable, as it is usage that should directly affect STDs, and not just having a distribution program. But we must also assume *condis* is exogenous in the *infrate*: in cannot be correlated with unobserved factors (in u_1) that also affect *infrate*.
We must also assume that *condis* has some partial effect on *conuse*, something that can be tested by estimating the reduced form for *conuse*. It seems likely that this requirement for an IV - see equations (15.30) and (15.31) - is satisfied.