Due Dec. 8th, by 2 pm in the Economics Office, SS 454. The office is closed during lunch hour, noon – 1 pm.

Please remember to do a cover sheet with your name, the course number, number all the pages, clearly label which question and part you are answering, and staple your assignment.

Submit your complete log file from Stata for every computer exercise into the D2L dropbox.

All page numbers refer to "*Introductory Econometrics, A Modern Approach*", 5th edition by Jeffrey M. Wooldridge.

Part A: - Chapter 12 – Problem 1, page 440

12.1 We can reason this from equation (12.4) because the usual OLS standard error is an estimate of $\sigma / \sqrt{SST_x}$. When the dependent and independent variables are in level (or log) form, the AR(1) parameter, ρ, tends to be positive in time series regression models. Further, the independent variables tend to be positive correlated, so $(x_t - \bar{x})(x_{t+j} - \bar{x})$ – which is what generally appears in (12.4) when the $\{x_t\}$ do not have zero sample average – tends to be positive for most t and j. With multiple explanatory variables the formulas are more complicated but have similar features.

If $\rho < 0$, or if the $\{x_t\}$ is negatively autocorrelated, the second term in the last line of (12.4) could be negative, in which case the true standard deviation of $\hat{\beta}_1$ is actually less than $\sigma / \sqrt{SST_x}$

$$var(\widehat{\beta_1}) = \frac{\sigma^2}{SST_X} + 2\frac{\sigma^2}{SST_X{}^2}\sum_{t=1}^{n-1}\sum_{j=1}^{n-1}\rho^j x_t x_{t+j}, \quad \text{Equation 12.4}$$

where $\sigma^2 = var(u_t)$.]

- Chapter 12 - Computer Exercise C2, page 442

C12.2 (i) After estimating the FDL model by OLS, we obtain the residuals and run the regression $\hat{u}_t$ on $\hat{u}_{t-1}$, using 272 observations. We get $\hat{\rho} \approx .503$ and $t_{\hat{\rho}} \approx 9.60$, which is very strong evidence of positive AR(1) correlation.

```
regress gprice gwage gwage_1 gwage_2 gwage_3 gwage_4 gwage_5 gwage_6 gwage_7 gwage_8
gwage_9 gwage_10 gwage_11 gwage_12
      Source |       SS       df       MS              Number of obs =     273
-------------+------------------------------           F( 13,   259) =    9.25
       Model |  .000981458    13  .000075497           Prob > F      =  0.0000
    Residual |  .002113658   259  8.1608e-06           R-squared     =  0.3171
-------------+------------------------------           Adj R-squared =  0.2828
       Total |  .003095116   272  .000011379           Root MSE      =  .00286
------------------------------------------------------------------------------
      gprice |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
```

```
       gwage |   .1190416   .0517725     2.30   0.022     .0170929    .2209903
     gwage_1 |   .0972174   .0390409     2.49   0.013     .0203393    .1740954
     gwage_2 |   .0399518   .0390717     1.02   0.307    -.0369869    .1168905
     gwage_3 |   .0382652   .0391513     0.98   0.329    -.0388301    .1153605
     gwage_4 |   .0813362   .0393483     2.07   0.040     .0038528    .1588195
     gwage_5 |    .106852   .0391937     2.73   0.007     .0296731    .1840308
     gwage_6 |   .0949731   .0392186     2.42   0.016     .0177451    .1722011
     gwage_7 |   .1037922   .0393788     2.64   0.009     .0262488    .1813355
     gwage_8 |   .1025629   .0394884     2.60   0.010     .0248037     .180322
     gwage_9 |   .1585079   .0393341     4.03   0.000     .0810526    .2359632
    gwage_10 |   .1104412   .0392229     2.82   0.005     .0332049    .1876776
    gwage_11 |   .1033206   .0394388     2.62   0.009     .0256591     .180982
    gwage_12 |   .0156575   .0518343     0.30   0.763    -.0864128    .1177278
       _cons |  -.0009296   .0005662    -1.64   0.102    -.0020445    .0001853
------------------------------------------------------------------------------

predict uhat, resid
(13 missing values generated)

regress uhat l.uhat
      Source |       SS       df       MS              Number of obs =     272
-------------+------------------------------           F(  1,   270) =   92.08
       Model |  .000534051     1  .000534051           Prob > F      =  0.0000
    Residual |  .001565989   270  5.8000e-06           R-squared     =  0.2543
-------------+------------------------------           Adj R-squared =  0.2515
       Total |  .002100039   271  7.7492e-06           Root MSE      =  .00241

------------------------------------------------------------------------------
        uhat |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        uhat |
         L1. |   .5026813   .0523858     9.60   0.000     .3995446     .605818
             |
       _cons |   .0000143    .000146     0.10   0.922    -.0002732    .0003018
------------------------------------------------------------------------------
```

(ii) When we estimate the model by iterated C-O, the LRP is estimated to be about 1.110.

```
prais gprice gwage gwage_1 gwage_2 gwage_3 gwage_4 gwage_5 gwage_6 gwage_7 gwage_8
gwage_9 gwage_10 gwage_11 gwage_12, rhotype(regress) corc

Iteration 0:  rho = 0.0000
Iteration 1:  rho = 0.5027
Iteration 2:  rho = 0.5085
Iteration 3:  rho = 0.5086
Iteration 4:  rho = 0.5086
Iteration 5:  rho = 0.5086

Cochrane-Orcutt AR(1) regression -- iterated estimates
      Source |       SS       df       MS              Number of obs =     272
-------------+------------------------------           F( 13,   258) =    3.52
       Model |  .000276359    13  .000021258           Prob > F      =  0.0000
    Residual |  .001559753   258  6.0456e-06           R-squared     =  0.1505
-------------+------------------------------           Adj R-squared =  0.1077
       Total |  .001836112   271  6.7753e-06           Root MSE      =  .00246

------------------------------------------------------------------------------
      gprice |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       gwage |   .0791942   .0415638     1.91   0.058    -.0026533    .1610417
     gwage_1 |   .0726127    .040009     1.81   0.071    -.0061731    .1513984
     gwage_2 |   .0239012   .0410998     0.58   0.561    -.0570325    .1048349
     gwage_3 |   .0334177   .0410322     0.81   0.416     -.047383    .1142183
```

```
     gwage_4 |   .0800965   .0410233     1.95   0.052    -.0006866    .1608796
     gwage_5 |   .1132117    .041008     2.76   0.006     .0324587    .1939647
     gwage_6 |   .0971594   .0412238     2.36   0.019     .0159814    .1783375
     gwage_7 |   .1010774   .0414903     2.44   0.016     .0193746    .1827801
     gwage_8 |   .1063414   .0415488     2.56   0.011     .0245235    .1881593
     gwage_9 |   .1609493   .0416366     3.87   0.000     .0789585    .2429401
    gwage_10 |   .1120996   .0416416     2.69   0.008     .0300989    .1941002
    gwage_11 |   .0995412   .0406007     2.45   0.015     .0195903    .1794921
    gwage_12 |   .0301766   .0415418     0.73   0.468    -.0516277    .1119808
       _cons |  -.0005979   .0009768    -0.61   0.541    -.0025214    .0013256
-------------+----------------------------------------------------------------
         rho |   .5086459
------------------------------------------------------------------------------
Durbin-Watson statistic (original)    0.988224
Durbin-Watson statistic (transformed) 2.211335
```

(iii) We use the same trick as in Problem 11.5, except now we estimate the equation by iterated C-O. In particular, write

$$gprice_t \;=\; \alpha_0 + \theta_0 gwage_t + \delta_1(gwage_{t-1} - gwage_t) + \delta_2(gwage_{t-2} - gwage_t)$$
$$+ \ldots + \delta_{12}(gwage_{t-12} - gwage_t) + u_t,$$

Where θ_0 is the LRP and $\{u_t\}$ is assumed to follow an AR(1) process. Estimating this equation by C-O gives $\hat{\theta}_0 \approx 1.110$ and se($\hat{\theta}_0$) $\approx$ .191. The t statistic for testing H_0: $\theta_0 = 1$ is (1.110 – 1)/.191 $\approx$ .58, which is not close to being significant at the 5% level. So the LRP is not statistically different from one.

```
*Generate 12 new variables
gen tgwage1= gwage_1- gwage
(2 missing values generated)

prais gprice gwage tgwage1 tgwage2 tgwage3 tgwage4 tgwage5 tgwage6 tgwage7 tgwage8
tgwage9 tgwage10 tgwage11 tgwage12, rhotype(regress) corc

Iteration 0:  rho = 0.0000
Iteration 1:  rho = 0.5027
Iteration 2:  rho = 0.5085
Iteration 3:  rho = 0.5086
Iteration 4:  rho = 0.5086
Iteration 5:  rho = 0.5086

Cochrane-Orcutt AR(1) regression -- iterated estimates
      Source |       SS       df       MS              Number of obs =     272
-------------+------------------------------           F( 13,   258) =    3.52
       Model |  .000276359    13  .000021258           Prob > F      =  0.0000
    Residual |  .001559753   258  6.0456e-06           R-squared     =  0.1505
-------------+------------------------------           Adj R-squared =  0.1077
       Total |  .001836112   271  6.7753e-06           Root MSE      =  .00246
------------------------------------------------------------------------------
      gprice |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       gwage |   1.109779   .1906803     5.82   0.000     .7342908    1.485266
     tgwage1 |   .0726127    .040009     1.81   0.071    -.0061731    .1513984
     tgwage2 |   .0239012   .0410998     0.58   0.561    -.0570325    .1048349
     tgwage3 |   .0334177   .0410322     0.81   0.416     -.047383    .1142183
     tgwage4 |   .0800965   .0410233     1.95   0.052    -.0006866    .1608796
     tgwage5 |   .1132117    .041008     2.76   0.006     .0324587    .1939647
```

```
     tgwage6 |   .0971594   .0412238     2.36   0.019     .0159814    .1783375
     tgwage7 |   .1010774   .0414903     2.44   0.016     .0193746    .1827801
     tgwage8 |   .1063414   .0415488     2.56   0.011     .0245235    .1881593
     tgwage9 |   .1609493   .0416366     3.87   0.000     .0789585    .2429401
    tgwage10 |   .1120996   .0416416     2.69   0.008     .0300989    .1941002
    tgwage11 |   .0995412   .0406007     2.45   0.015     .0195903    .1794921
    tgwage12 |   .0301766   .0415418     0.73   0.468    -.0516277    .1119808
       _cons |  -.0005979   .0009768    -0.61   0.541    -.0025214    .0013256
-------------+----------------------------------------------------------------
         rho |   .5086459
------------------------------------------------------------------------------
Durbin-Watson statistic (original)    0.988224
Durbin-Watson statistic (transformed) 2.211335
```

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- Chapter 13 – Problem 5, page 475

13.5 No, we cannot include age as an explanatory variable in the original model. Each person in the panel data set is exactly two years older on January 31, 1992 than on January 31, 1990. This means that $\Delta age_i = 2$ for all i. But the equation we would estimate is of the form

$$\Delta saving_i = \delta_0 + \beta_1 \Delta age_i + \ldots,$$

where δ_0 is the coefficient the year dummy for 1992 in the original model. As we know, when we have an intercept in the model we cannot include an explanatory variable that is constant across i; this violates Assumption MLR.3. Intuitively, since age changes by the same amount for everyone, we cannot distinguish the effect of age from the aggregate time effect.

- Chapter 13 – Computer Exercise C7, page 478

C13.7 (i) Pooling across semesters and using OLS gives

$$\begin{aligned} trmgpa = {} & \underset{(0.35)}{-1.75} - \underset{(.048)}{.058}\, spring + \underset{(.00015)}{.00170}\, sat - \underset{(.0010)}{.0087}\, hsperc + \underset{(.052)}{.350}\, female - \underset{(.123)}{.254}\, black \\ & - \underset{(.117)}{.023}\, white - \underset{(.076)}{.035}\, frstsem - \underset{(.00073)}{.00034}\, tothrs + \underset{(0.104)}{1.048}\, crsgpa - \underset{(.049)}{.027}\, season \end{aligned}$$

$$n = 732, \quad R^2 = .478, \quad \bar{R}^2 = .470.$$

The coefficient on *season* implies that, other things fixed, an athlete's term GPA is about .027 points lower when his/her sport is in season. On a four point scale, this a modest effect (although it accumulates over four years of athletic eligibility). However, the estimate is not statistically significant (t statistic $\approx -.55$).

```
regress trmgpa spring sat hsperc female black white frstsem crsgpa season

      Source |       SS       df       MS              Number of obs =     732
-------------+------------------------------           F(  9,   722) =   73.29
       Model |  200.651854     9  22.2946504           Prob > F      =  0.0000
    Residual |  219.645102   722  .304217593           R-squared     =  0.4774
-------------+------------------------------           Adj R-squared =  0.4709
       Total |  420.296956   731  .574961636           Root MSE      =  .55156
```

```
------------------------------------------------------------------------------
     trmgpa |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      spring |  -.0578682   .0480099    -1.21   0.228    -.1521238    .0363874
         sat |   .0017051   .0001487    11.47   0.000     .0014132    .0019969
      hsperc |  -.0085867   .0010234    -8.39   0.000    -.0105959   -.0065775
      female |   .3514068   .0517795     6.79   0.000     .2497504    .4530632
       black |   -.257919   .1225891    -2.10   0.036    -.4985927   -.0172453
       white |  -.0258349   .1172074    -0.22   0.826    -.2559429    .2042732
     frstsem |  -.0196012   .0688027    -0.28   0.776    -.1546784    .1154759
      crsgpa |   1.033563    .099442    10.39   0.000     .8383334    1.228793
      season |  -.0270841   .0490175    -0.55   0.581    -.1233179    .0691497
       _cons |  -1.737375   .3461319    -5.02   0.000    -2.416921    -1.05783
------------------------------------------------------------------------------
```

(ii) The quick answer is that if omitted ability is correlated with *season* then, as we know from Chapters 3 and 5, OLS is biased and inconsistent. The fact that we are pooling across two semesters does not change that basic point.

If we think harder, the direction of the bias is not clear, and this is where pooling across semesters plays a role. First, suppose we used only the fall term, when football is in season. Then the error term and season would be negatively correlated, which produces a downward bias in the OLS estimator of β_{season}. Because β_{season} is hypothesized to be negative, an OLS regression using only the fall data produces a downward biased estimator. [When just the fall data are used, $\hat{\beta}_{season}$ = –.116 (se = .084), which is in the direction of more bias.] However, if we use just the spring semester, the bias is in the opposite direction because ability and season would be positive correlated (more academically able athletes are in season in the spring). In fact, using just the spring semester gives $\hat{\beta}_{season}$ = .00089 (se = .06480), which is practically and statistically equal to zero. When we pool the two semesters we cannot, with a much more detailed analysis, determine which bias will dominate.

(iii) The variables *sat*, *hsperc*, *female*, *black*, and *white* all drop out because they do not vary by semester. The intercept in the first-differenced equation is the intercept for the spring. We have

$$\Delta trmgpa = -.237 + .019\,\Delta frstsem + .012\,\Delta tothrs + 1.136\,\Delta crsgpa - .065\,\Delta season \quad R^2 = .208$$
$$(.206) \quad (.069) \quad (.014) \quad (0.119) \quad (.043) \quad \bar{R}^2 = .199,\ n = 366$$

Interestingly, the in-season effect is larger now: term GPA is estimated to be about .065 points lower in a semester that the sport is in-season. The *t* statistic is about –1.51, which gives a one-sided *p*-value of about .065.

```
regress ctrmgpa cfrstsem ctothrs ccrsgpa cseason

      Source |       SS       df       MS              Number of obs =     366
-------------+------------------------------           F(  4,   361) =   23.70
       Model |  31.7194521     4  7.92986302           Prob > F      =  0.0000
    Residual |  120.771129   361  .334546063           R-squared     =  0.2080
-------------+------------------------------           Adj R-squared =  0.1992
       Total |  152.490581   365  .417782414           Root MSE      =   .5784

------------------------------------------------------------------------------
     ctrmgpa |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
```

```
    cfrstsem |   .0191468   .0692659     0.28   0.782    -.1170684    .1553621
     ctothrs |   .0121541   .0143912     0.84   0.399     -.016147    .0404551
     ccrsgpa |   1.136355   .1188117     9.56   0.000     .9027046    1.370004
     cseason |  -.0645034   .0425217    -1.52   0.130    -.1481247     .019118
       _cons |  -.2365608   .2059696    -1.15   0.252    -.6416117    .1684902
------------------------------------------------------------------------------
```

(iv) One possibility is a measure of course load. If some fraction of student-athletes take a lighter load during the season (for those sports that have a true season), then term GPAs may tend to be higher, other things equal. This would bias the results away from finding an effect of *season* on term GPA.

Part B: - Chapter 14 – Problem 5, page 503

14.5 (i) For each student we have several measures of performance, typically three or four, the number of classes taken by a student that have final exams. When we specify an equation for each standardized final exam score, the errors in the different equations for the same student are certain to be correlated: students who have more (unobserved) ability tend to do better on all tests.

(ii) An unobserved effects model is

$$score_{sc} = \theta_c + \beta_1 atndrte_{sc} + \beta_2 major_{sc} + \beta_3 SAT_s + \beta_4 cumGPA_s + a_s + u_{sc},$$

where a_s is the unobserved student effect. Because SAT score and cumulative GPA depend only on the student, and not on the particular class he/she is taking, these do not have a *c* subscript. The attendance rates do generally vary across class, as does the indicator for whether a class is in the student's major. The term θ_c denotes different intercepts for different classes. Unlike with a panel data set, where time is the natural ordering of the data within each cross-sectional unit, and the aggregate time effects apply to all units, intercepts for the different classes may not be needed. If all students took the same set of classes then this is similar to a panel data set, and we would want to put in different class intercepts. But with students taking different courses, the class we label as "1" for student A need have nothing to do with class "1" for student B. Thus, the different class intercepts based on arbitrarily ordering the classes for each student probably are not needed. We can replace θ_c with β_0, an intercept constant across classes.

(iii) Maintaining the assumption that the idiosyncratic error, u_{sc}, is uncorrelated with all explanatory variables, we need the unobserved student heterogeneity, a_s, to be uncorrelated with $atndrte_{sc}$. The inclusion of SAT score and cumulative GPA should help in this regard, as a_s, is the part of ability that is not captured by SAT_s and $cumGPA_s$. In other words, controlling for SAT_s and $cumGPA_s$ could be enough to obtain the ceteris paribus effect of class attendance.

(iv) If SAT_s and $cumGPA_s$ are not sufficient controls for student ability and motivation, a_s is correlated with $atndrte_{sc}$, and this would cause pooled OLS to be biased and inconsistent. We could use fixed effects instead. Within each student we compute the demeaned data, where, for each student, the means are computed across classes. The variables SAT_s and $cumGPA_s$ drop out of the analysis.

- Chapter 14 - Computer Exercise C7, page 505

C14.7 (i) If there is a deterrent effect then $\beta_1 < 0$. The sign of β_2 is not entirely obvious, although one possibility is that a better economy means less crime in general, including violent crime (such as drug dealing) that would lead to fewer murders. This would imply $\beta_2 > 0$.

(ii) The pooled OLS estimates using 1990 and 1993 are

$$\underset{}{mrdrte_{it}} = \underset{(4.43)}{-5.28} - \underset{(2.14)}{2.07}\, d93_t + \underset{(.263)}{.128}\, exec_{it} + \underset{(0.78)}{2.53}\, unem_{it} \qquad R^2 = .102, \quad N = 51,\ T = 2,$$

There is no evidence of a deterrent effect, as the coefficient on *exec* is actually positive (though not statistically significant).

```
iis id
tis year

regress mrdrte d93 exec unem if year==90|year==93

      Source |       SS       df       MS              Number of obs =     102
-------------+------------------------------           F(  3,    98) =    3.69
       Model |  1158.49706     3  386.165687           Prob > F      =  0.0144
    Residual |  10242.7183    98  104.517533           R-squared     =  0.1016
-------------+------------------------------           Adj R-squared =  0.0741
       Total |  11401.2153   101   112.88332           Root MSE      =  10.223

------------------------------------------------------------------------------
      mrdrte |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         d93 |  -2.067417   2.144634    -0.96   0.337    -6.323373    2.188538
        exec |   .1277287   .2632353     0.49   0.629    -.3946532    .6501105
        unem |   2.528892    .781723     3.24   0.002     .9775877    4.080196
       _cons |  -5.278005   4.427805    -1.19   0.236    -14.06484     3.50883
------------------------------------------------------------------------------
```

(iii) The first-differenced equation is

$$\Delta mrdrte_i = \underset{(.209)}{.413} - \underset{(.043)}{.104}\, \Delta exec_i - \underset{(.159)}{.067}\, \Delta unem_i \qquad R^2 = .110, \quad n = 51$$

Now, there is a statistically significant deterrent effect: 10 more executions is estimated to reduce the murder rate by 1.04, or one murder per 100,000 people. Is this a large effect? Executions are relatively rare in most states, but murder rates are relatively low on average, too. In 1993, the average murder rate was about 8.7; a reduction of one would be nontrivial. For the (unknown) people whose lives might be saved via a deterrent effect, it would seem important.

regress cmrdrte cexec cunem if year==93

```
      Source |       SS       df       MS              Number of obs =      51
-------------+------------------------------           F(  2,    48) =    2.96
       Model |   6.8879023     2  3.44395115           Prob > F      =  0.0614
    Residual |  55.8724857    48  1.16401012           R-squared     =  0.1097
-------------+------------------------------           Adj R-squared =  0.0727
       Total |   62.760388    50  1.25520776           Root MSE      =  1.0789
```

```
------------------------------------------------------------------------------
     cmrdrte |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       cexec |  -.1038396   .0434139    -2.39   0.021    -.1911292     -.01655
       cunem |  -.0665914   .1586859    -0.42   0.677    -.3856509     .252468
       _cons |   .4132665   .2093848     1.97   0.054    -.0077298    .8342628
------------------------------------------------------------------------------
```

(iv) The heteroskedasticity-robust standard error for *exec* is 0.134 if we re-estimate the model in part (ii). This is almost half the value of the nonrobust standard error. If we use the robust standard error, there is no statistical evidence for the deterrent effect, ($t \approx 0.95$).

The heteroskedasticity-robust standard error for $\Delta exec_i$ is .017 if we re-estimate the model in part (iii). Somewhat surprisingly, this is well below the nonrobust standard error. If we use the robust standard error, the statistical evidence for the deterrent effect is quite strong ($t \approx -6.1$). *See also Computer Exercise 13.12.*

```
regress mrdrte d93 exec unem if year==90|year==93, robust

Linear regression                                      Number of obs =     102
                                                       F(  3,    98) =   10.74
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.1016
                                                       Root MSE      =  10.223

------------------------------------------------------------------------------
             |               Robust
      mrdrte |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         d93 |  -2.067417    1.99811    -1.03   0.303    -6.032601    1.897767
        exec |   .1277287   .1342426     0.95   0.344    -.1386714    .3941287
        unem |   2.528892   1.107556     2.28   0.025     .3309826    4.726801
       _cons |  -5.278005   5.386767    -0.98   0.330    -15.96787    5.411859
------------------------------------------------------------------------------

. regress cmrdrte  cexec cunem if year==93, robust

Linear regression                                      Number of obs =      51
                                                       F(  2,    48) =   18.92
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.1097
                                                       Root MSE      =  1.0789

------------------------------------------------------------------------------
             |               Robust
     cmrdrte |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       cexec |  -.1038396   .0169995    -6.11   0.000    -.1380194   -.0696598
       cunem |  -.0665914     .14693    -0.45   0.652    -.3620141    .2288312
       _cons |   .4132665   .2000057     2.07   0.044     .0111281    .8154049
```

(v) Texas had by far the largest value of *exec*, 34. The next highest state was Virginia, with 11. These are three-year totals.

(vi) Without Texas in the estimation, we get the following, with heteroskedasticity-robust standard errors in [·]:

$$\Delta mrdrte_i = .413 - .067\,\Delta exec_i - .070\,\Delta unem_i \qquad R^2 = .013$$
$$\quad\;(.211)\quad(.105)\qquad\quad(.160)\qquad\qquad n = 50$$
$$\quad\;[.200]\quad[.079]\qquad\quad[.146]$$

Now the estimated deterrent effect is smaller. Perhaps more importantly, the standard error on $\Delta exec_i$ has increased by a substantial amount. This happens because when we drop Texas, we lose much of the variation in the key explanatory variable, $\Delta exec_i$.

```
regress cmrdrte  cexec cunem if year==93&id!=44

      Source |       SS       df       MS              Number of obs =      50
-------------+------------------------------           F(  2,    47) =    0.32
       Model |  .755191109     2  .377595555           Prob > F      =  0.7287
    Residual |  55.7000012    47  1.18510641           R-squared     =  0.0134
-------------+------------------------------           Adj R-squared = -0.0286
       Total |  56.4551923    49  1.15214678           Root MSE      =  1.0886

------------------------------------------------------------------------------
     cmrdrte |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       cexec |   -.067471    .104913    -0.64   0.523    -.2785288    .1435868
       cunem |  -.0700316   .1603712    -0.44   0.664    -.3926569    .2525936
       _cons |   .4125226   .2112827     1.95   0.057    -.0125233    .8375686
```

```
regress cmrdrte  cexec cunem if year==93&id!=44, robust

Linear regression                                      Number of obs =      50
                                                       F(  2,    47) =    0.54
                                                       Prob > F      =  0.5846
                                                       R-squared     =  0.0134
                                                       Root MSE      =  1.0886

------------------------------------------------------------------------------
             |               Robust
     cmrdrte |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       cexec |   -.067471   .0790993    -0.85   0.398    -.2265983    .0916563
       cunem |  -.0700316   .1462091    -0.48   0.634    -.3641663    .2241031
       _cons |   .4125226   .2004375     2.06   0.045     .0092943     .815751
```

(vii) When we apply fixed effects using all three years of data and all states we get

$$mrdrte_{it} = 5.82 + 1.56\, d90_t + 1.73\, d93_t - .138\, exec_{it} + .221\, unem_{it} \qquad R^2 = .073$$
$$(1.92)\quad(.75)\qquad(.70)\qquad(.177)\qquad(.296)\qquad N = 51,\; T = 3$$

The size of the deterrent effect is actually slightly larger than when 1987 is not used. However, the t statistic is only about –.78. Thus, while the magnitude of the effect is similar, the statistical significance is not. It is somewhat odd that adding another year of data causes the standard error on the *exec* coefficient to increase nontrivially.

```
. xtreg mrdrte exec unem d2 d3, fe

Fixed-effects (within) regression               Number of obs      =       153
Group variable: id                              Number of groups   =        51

R-sq:  within  = 0.0734                         Obs per group: min =         3
```

```
       between = 0.0037                                         avg =        3.0
       overall = 0.0108                                         max =          3

                                                F(4,98)            =       1.94
corr(u_i, Xb)  = 0.0010                         Prob > F           =     0.1098

------------------------------------------------------------------------------
      mrdrte |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        exec |  -.1383231   .1770059    -0.78   0.436    -.4895856    .2129395
        unem |   .2213158   .2963756     0.75   0.457     -.366832    .8094636
          d2 |   1.556215   .7453273     2.09   0.039     .0771369    3.035293
          d3 |   1.733242   .7004381     2.47   0.015     .3432454    3.123239
       _cons |   5.822104   1.915611     3.04   0.003     2.020636    9.623572
-------------+----------------------------------------------------------------
     sigma_u |  8.7527226
     sigma_e |  3.5214244
         rho |  .86068589   (fraction of variance due to u_i)
------------------------------------------------------------------------------
F test that all u_i=0:     F(50, 98) =    17.18             Prob > F = 0.0000
```

MM 01/12/15