Panel Data

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1. Guns is a balanced panel of data on 50 US states, plus the District of Columbia (for a total of 51 states), by year for 1977Ð1999. A data frame containing 1,173 observations on 13 variables:

   - *state*: factor indicating state.
   - *year*: factor indicating year.
   - *violent*: violent crime rate (incidents per 100,000 members of the population).
   - *murder*: murder rate (incidents per 100,000).
   - *robbery*: robbery rate (incidents per 100,000).
   - *prisoners*: incarceration rate in the state in the previous year (sentenced prisoners per 100,000 residents; value for the previous year).
   - $afam$: percent of state population that is African-American, ages 10 to 64.
   - *cauc*: percent of state population that is Caucasian, ages 10 to 64.
   - *male*: percent of state population that is male, ages 10 to 29.
   - *population*: state population, in millions of people.
   - *income*: real per capita personal income in the state (US dollars).
   - *density*: population per square mile of land area, divided by 1,000.
   - *shall*: Does the state have a shall carry law in effect in that year?

Some U.S. states have enacted lows that allow citizens to carry concealed weapons. These laws are known as Òshall-issueÓ laws because they instruct local authorities to issue a concealed weapons permit to all applicants who are citizens , mentally competent, and have not been convicted of a felony (some state have additional restrictions). Proponents argue that, if more people carry concealed weapons, crime will decline because criminals are deterred from attacking other people. Opponents argue that crime will increase because of accidental or spontaneous use of the weapon. In this exercise, you will analyze the effect of concealed weapons laws on violent crimes.

Estimate (1) an OLS regression under heteroschedasticity using MatLab of $ln(violent)$ against $shall$ and a (2) regression of $ln(violent)$ against $shall$, $prisoners$, $density$, $income$, $population$, $afam$, $cauc$ and $male$.(You need as output β and t)

(a) Interpret the coefficient on shall in regression (1) and (2). Is this estimate large or small in "real-world" sense?

Does adding the control variables in regression (2) changes the estimated effect of a shall-carry law in regression (1), as measured by statistical significance? As measured by "real-world" significance of the estimated coefficient?

Solution: If you regress $ln(violent)$ on $shall$ you will have this output:

```
Linear regression                                      Number of obs =     1173
                                                       F(  1,  1171) =    86.86
                                                       Prob > F      =   0.0000
                                                       R-squared     =   0.0866
                                                       Root MSE      =   .61735

------------------------------------------------------------------------------
             |               Robust
    lviolent |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       shall |  -.4429646   .0475283    -9.32   0.000    -.5362148   -.3497144
       _cons |   6.134919   .0193039   317.81   0.000     6.097045    6.172793
------------------------------------------------------------------------------
```

If we run second regression we will have this output:

```
Linear regression                                      Number of obs =    1173
                                                       F(  8,  1164) =   95.67
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.5643
                                                       Root MSE      =  .42769

------------------------------------------------------------------------------
             |               Robust
    lviolent |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       shall |  -.3683869   .0347879   -10.59   0.000     -.436641   -.3001329
   prisoners |   .0016126   .0001807     8.92   0.000     .0012581    .0019672
     density |   .0266885   .0143494     1.86   0.063    -.0014651     .054842
      income |   .0012051   .0072778     0.17   0.869     -.013074    .0154842
  population |   .0427098   .0031466    13.57   0.000     .0365361    .0488836
        afam |   .0808526   .0199924     4.04   0.000     .0416274    .1200778
        cauc |   .0312005   .0097271     3.21   0.001      .012116    .0502851
        male |   .0088709   .0120604     0.74   0.462    -.0147917    .0325334
       _cons |   2.981738   .6090198     4.90   0.000     1.786839    4.176638
------------------------------------------------------------------------------
```

(b) Add state fixed effects to your MatLab regression. Do both using Dummy variables for state and using the partitioned regression. Do the result change when you add fixed state effect? If so, which set of regression results is more credible and why? Do the results change when you use dummy or partition?

Solution:

```
Linear regression, absorbing indicators             Number of obs =     1173
                                                    F(  8,  1114) =    38.77
                                                    Prob > F      =   0.0000
                                                    R-squared     =   0.9411
                                                    Adj R-squared =   0.9380
                                                    Root MSE      =   .16072

------------------------------------------------------------------------------
    lviolent |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       shall |  -.0461415   .0188668    -2.45   0.015      -.08316    -.009123
   prisoners |   -.000071   .0000936    -0.76   0.448    -.0002547    .0001126
     density |  -.1722901   .0850362    -2.03   0.043    -.3391392   -.0054409
      income |  -.0092037   .0059083    -1.56   0.120    -.0207963    .0023889
  population |   .0115247   .0087239     1.32   0.187    -.0055924    .0286417
        afam |   .1042804   .0177564     5.87   0.000     .0694407    .1391201
        cauc |   .0408611   .0050745     8.05   0.000     .0309044    .0508177
        male |  -.0502725   .0064037    -7.85   0.000    -.0628373   -.0377078
       _cons |   3.866017   .3847716    10.05   0.000     3.111058    4.620975
-------------+----------------------------------------------------------------
       state |       F(50, 1114) =    142.570   0.000          (51 categories)
```

(c) Add time fixed effect to the previous regression both using the dummy variables for time and the "double partition" (derivation should be done by you!). Do the results change when you add fixed time effects? If so, which set of regression is more credible and why? (Pay attention when you add the time dummy variables).

Solution: You will have this output (actually we put a shorter version):

```
Linear regression, absorbing indicators             Number of obs =     1173
                                                    F( 30,  1092) =    26.14
                                                    Prob > F      =   0.0000
                                                    R-squared     =   0.9562
                                                    Adj R-squared =   0.9530
                                                    Root MSE      =   .14003

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    lviolent |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       shall |  -.0279935   .0171578    -1.63   0.103    -.0616596    .0056725
   prisoners |    .000076   .0000903     0.84   0.400    -.0001012    .0002531
     density |   -.091555   .0762821    -1.20   0.230    -.2412312    .0581212
      income |   .0009587   .0064349     0.15   0.882    -.0116676    .0135849
  population |  -.0047544   .0078675    -0.60   0.546    -.0201916    .0106827
```

```
        afam |   .0291862    .022692     1.29   0.199    -.0153387    .0737111
        cauc |   .0092501   .0078617     1.18   0.240    -.0061756    .0246759
        male |   .0733254   .0156139     4.70   0.000     .0426887     .103962
------------------------------------------------------------------------------
```