

# MPP-C6: Statistics II

## Session ?

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15 October 2015



# Applying Panel Data Methods to Other Data Structures

## Motivation

- Panel data methods can be used with data structures that do not involve time
- Hierarchical data structures contain clusters of observation which share common characteristics
- When these characteristics are unobservable and correlated with other explanatory variables, pooled OLS will give us estimates that are biased and inefficient

# Applying Panel Data Methods to Other Data Structures

## Motivation

- Consider a geographical dataset that observes variables for small areas (in this case MSOAs, or Middle Layer Super Output Areas)
- Each small area belongs to a local authority
- If local authority attributes that we cannot observe affect our other variables, we will get biased and inefficient estimates using OLS

# Applying Panel Data Methods to Other Data Structures

## Motivation

Remember that OLS regression is estimated using the equation

$$y_i = \beta_0 + \beta_1 x_i + u_i$$

When we use panel methods across time, our equation becomes

$$y_{it} = \beta_0 + \beta_1 x_{it} + a_i + u_{it}$$

Here the variable  $a_i$  captures all unobserved, time-constant factors that affect  $y_{it}$

# Applying Panel Data Methods to Other Data Structures

## Motivation

By constructing our dataset and a fixed effects model carefully, we can also account for fixed effects given by local authorities with the equation

$$y_{pc} = \beta_0 + \beta_1 x_{pc} + a_p + u_{pc}$$

where, given our hierarchical data structure,  $p$  indexes the parent (local authority) and  $c$  indexes the child (MSOA)

Here the local authority fixed effect is given by  $a_p$ , and the coefficient  $\beta_1 x_{pc}$  describes the effect of our explanatory variable on our independent variable  $x$  *within* local authorities.

# Applying Panel Data Methods to Other Data Structures

## Pooled OLS

When we use a pooled OLS regression on our dataset to estimate the effect of income on household energy consumption, we get the following results

*Interactive Stata example*

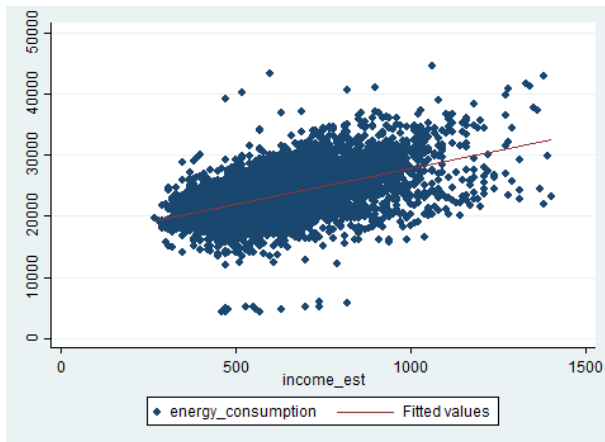
```
1 . reg energy_consumption income_est
2
3      Source |           SS           df           MS      Number of obs   =       7,133
4 -----+-----
5      Model |  2.6921e+10            1   2.6921e+10      F(1, 7131)         =     2766.55
6      Residual |  6.9391e+10         7,131   9730852.07      Prob > F           =       0.0000
7 -----+-----
8      Total |  9.6312e+10         7,132  13504151.6      R-squared          =       0.2795
9                                     Adj R-squared       =       0.2794
10                                    Root MSE           =       3119.4
11
12 -----+-----
13      energy_con~n |           Coef.      Std. Err.      t    P>|t|     [95% Conf. Interval]
14 -----+-----
15      income_est |    11.68066      .2220741     52.60   0.000     11.24533     12.11599
16      _cons |    16142.07     139.382     115.81   0.000    15868.84    16415.3
```

# Applying Panel Data Methods to Other Data Structures

## Pooled OLS

*Interactive Stata example*

```
1 graph twoway (scatter energy_consumption income_est) ///  
2 (lfit energy_consumption income_est)
```



# Applying Panel Data Methods to Other Data Structures

## Fixed Effects

When we use a fixed effects model to estimate the effect of income on household energy consumption *within* local authorities, the size of the effect changes.

*Interactive Stata example*

```
1 . xtreg energy_consumption income_est, fe
2
3 Fixed-effects (within) regression          Number of obs   =       7,133
4 Group variable: LA_CODE                   Number of groups  =        376
5
6 R-sq:                                     Obs per group:
7     within = 0.5160                      min =          1
8     between = 0.1057                     avg =         19.0
9     overall = 0.2795                     max =        131
10
11                                         F(1,6756)        =       7201.69
12 corr(u_i, Xb) = -0.5247                 Prob > F          =        0.0000
13
14 -----+-----
15 energy_con~n |          Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
16 -----+-----
17   income_est |   20.11081   .2369803    84.86   0.000    19.64625    20.57536
18     _cons |  11040.14   145.7513    75.75   0.000   10754.42   11325.86
19 -----+-----
20   sigma_u |  2773.6255
21   sigma_e |  2192.6781
22     rho |   .6153982   (fraction of variance due to u_i)
23 -----+-----
24 F test that all u_i=0: F(375, 6756) = 20.47                Prob > F = 0.0000
25
```

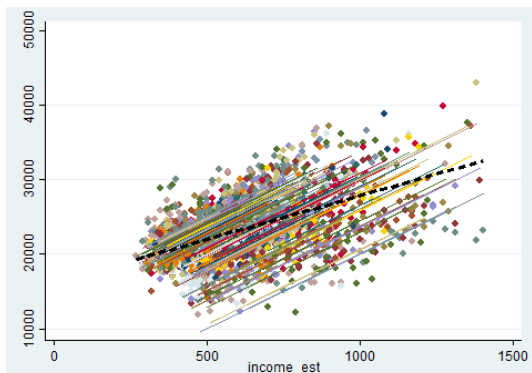


# Applying Panel Data Methods to Other Data Structures

## Fixed Effects

*Interactive Stata example*

```
1 . xi: regress energy_consumption income_est i.LA_CODE
2 . predict energy_consumption_fitted
3 (option xb assumed; fitted values)
4 . separate energy_consumption, by(LA_CODE)
5 . separate energy_consumption_fitted, by(LA_CODE)
6 . graph twoway (scatter energy_consumption1-energy_consumption80 income_est) ///
7 > (line energy_consumption_fitted1-energy_consumption_fitted80 income_est) ///
8 > (lfit energy_consumption income_est, ///
9 > color(black) lwidth(thick) lpattern(dash)), legend(off)
```



# Applying Panel Data Methods to Other Data Structures

## Comparing OLS with Fixed Effects Models

*Interactive Stata example*

```
1 . esttab ols fe
2
3 -----
4               (1)          (2)
5      energy_con~n  energy_con~n
6 -----
7 income_est      11.68***    20.11***
8                (52.60)     (84.86)
9
10 _cons          16142.1***   11040.1***
11                (115.81)    (75.75)
12 -----
13 N                7133       7133
14 -----
15 t statistics in parentheses
16 * p<0.05, ** p<0.01, *** p<0.001
```