

# Applying Panel Data Methods to Other Data Structures

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# 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  $y_{it}$

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## 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

```
reg energy_consumption income_est
outtex, file(ols.tex) labels level detail legend key(stab) replace est store ols
```

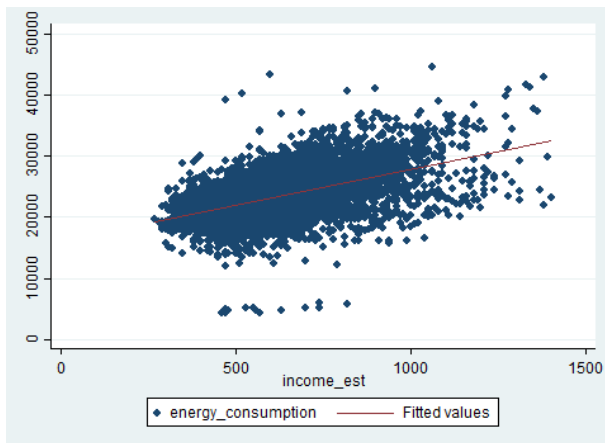
Table : Estimation results : regress

Variable	Coefficient	(Std. Err.)
income_est	11.681**	(0.222)
Intercept	16142.067**	(139.382)
<hr/>		
N	7133	
R <sup>2</sup>	0.28	
F (1,7131)	2766.551	
<hr/>		
Significance levels :	† : 10%	* : 5%      ** : 1%

# Applying Panel Data Methods to Other Data Structures

## Pooled OLS

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



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## 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.

```
xtset LA_CODE MSOA_CODE
xtreg energy_consumption income_est, fe
outtex, file(fe.tex) labels level detail legend key(stab) replace
est store fe
```

Table : Estimation results : xtreg

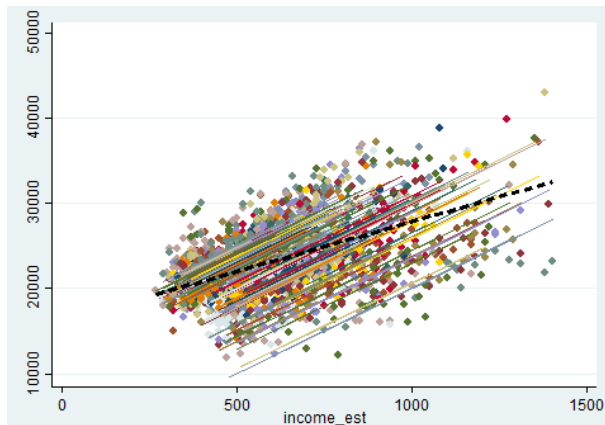
Variable	Coefficient	(Std. Err.)
income_est	20.111**	(0.237)
Intercept	11040.143**	(145.751)
<hr/>		
N	7133	
R <sup>2</sup>	0.516	
F <sub>(376,6756)</sub>	7201.692	
<hr/>		
Significance levels :    † : 10%       * : 5%       ** : 1%		



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## Fixed Effects

```
xi: regress energy_consumption income_est i.LA_CODE
predict energy_consumption_fitted
separate energy_consumption, by(LA_CODE)
separate energy_consumption_fitted, by(LA_CODE)
graph twoway (scatter energy_consumption1-energy_consumption80 income_est) ///
(line energy_consumption_fitted1-energy_consumption_fitted80 income_est) ///
(lfit energy_consumption income_est, ///
color(black) lwidth(thick) lpattern(dash)), legend(off) , legend(off)
```



# Applying Panel Data Methods to Other Data Structures

## Comparing OLS with Fixed Effects Models

```
esttab ols fe using table1.tex, replace
```

	(1)	(2)
	energy_consumption	energy_consumption
income_est	11.68*** (52.60)	20.11*** (84.86)
_cons	16142.1*** (115.81)	11040.1*** (75.75)
<i>N</i>	7133	7133

*t* statistics in parentheses

\*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$