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

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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

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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.

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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)
N	7133	
R^2	0.28	
$F_{(1,7131)}$	2766.551	

Significance levels : † : 10% * : 5% ** : 1%

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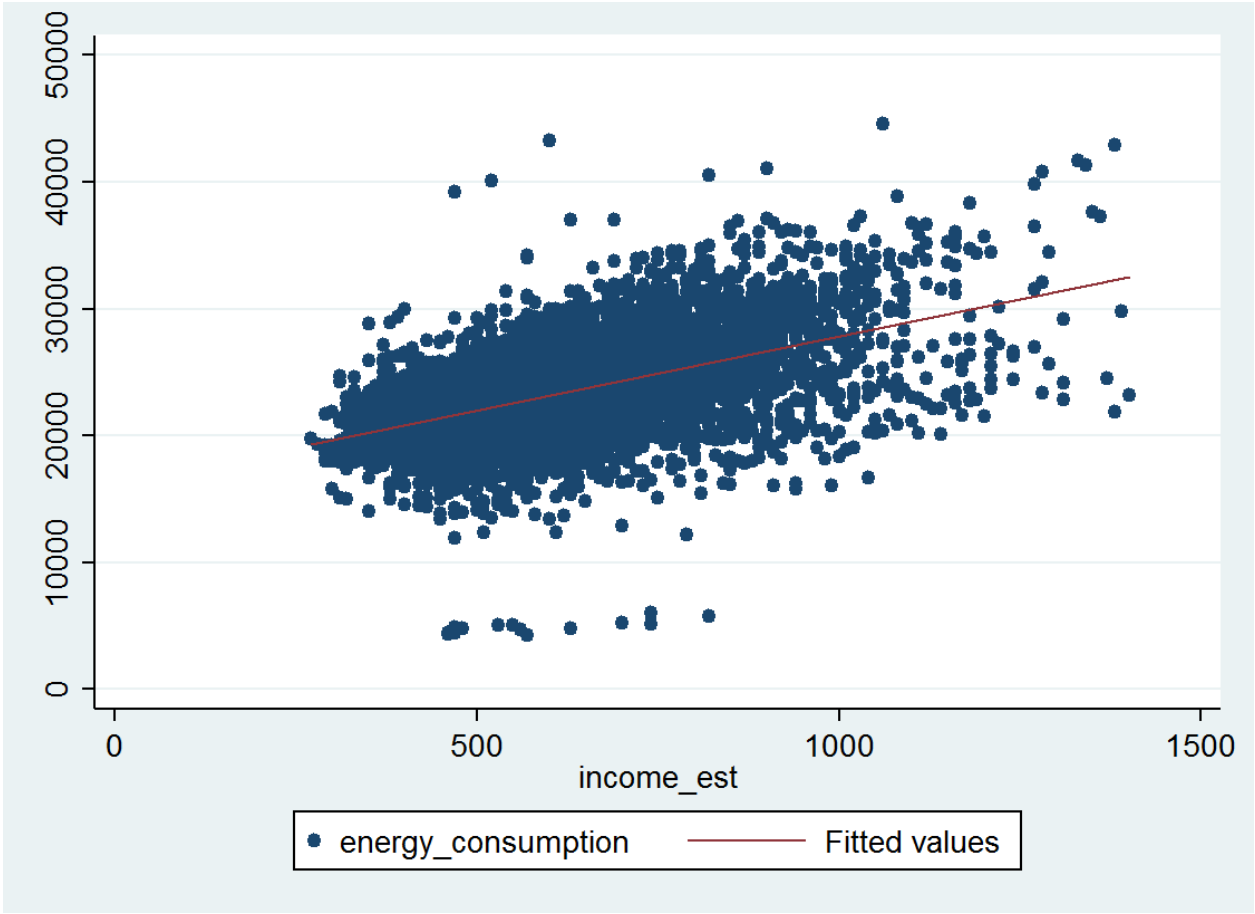
Pooled OLS

```
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)
N	7133	
R^2	0.516	
$F_{(376,6756)}$	7201.692	

Significance levels : † : 10% * : 5% ** : 1%

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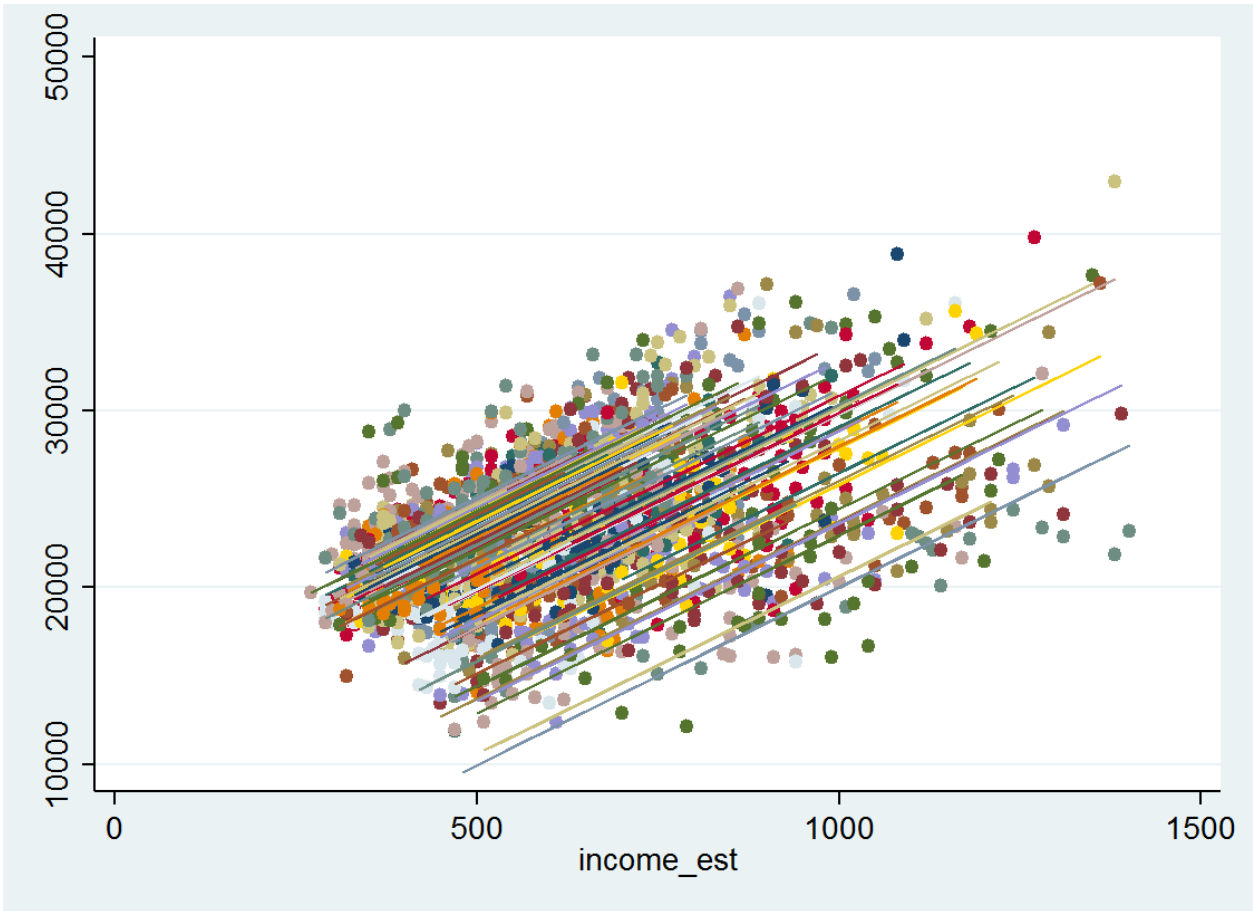
Fixed Effects

```
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_fit
income_est), legend(off)
```



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Comparing OLS with Fixed Effects Models

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

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

t statistics in parentheses

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