

# Panel Data Regression

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## Panel Data

Up to now we have analyzed either

- **Cross-sectional data** (data collected on several individuals/units at one point in time)

or

- **Time series data** (data collected on one individual/unit over several time periods)

What if we have a combination of these two types of data?

Panel data are repeated cross-sections over time, in essence there will be space as well as time dimensions.

Other names are *pooled data*, *micropanel data*, *longitudinal data*, *event history analysis* and *cohort analysis*

## Panel Data Examples

The individuals/units can for example be workers, firms, states or countries

- Annual unemployment rates of each state over several years
- Quarterly sales of individual stores over several quarters
- Wages for the same worker, working at several different jobs

## Panel Data Examples

Some american surveys:

- The National Longitudinal Survey of Youth (NLSY) tracks labor market outcomes for thousands of individuals, beginning in their teenage years
- The Panel Survey of Income Dynamics (PSID) since 1968 collects data on 5000 families about various socioeconomic and demographic variables
- The Survey of Income and Program Participation (SIPP), conducts interviews four times a year about the respondents economic conditions

# Panel Data

## Potential gains

- take heterogeneity into account, get individual-specific estimates
- especially suitable to study dynamics of change
- study more sophisticated behavioral models
- minimize bias due to aggregation

However, panel data also increases the complexity of the analysis.

# Panel Data

- Balanced/unbalanced
- Short panel/long panel

Two kinds of models:

FIXED EFFECTS MODELS

RANDOM EFFECTS MODELS

The two types of analyses make conceptually contrasting assumptions about effects as either random or fixed



Example with 2 explanatory variables:

$$Y_{it} = \beta_1 + \beta_2 X_{2it} + \beta_3 X_{3it} + u_{it}$$

Notice the subscript index **it**

- **i** stands for the  $i$  :  $th$  cross-sectional unit,  $i = 1, \dots, N$
- **t** stands for the  $t$  :  $th$  time period,  $t = 1, \dots, T$

## Pooled OLS Regression

Treats all observation as equivalent and OLS as usual

$$Y_{it} = \beta_1 + \beta_2 X_{2it} + \beta_3 X_{3it} + u_{it}$$

In this case the error term captures "everything"

Naive, ignores time and space

# Fixed Effects Models with Dummy Variables

Several kinds of fixed effects models, differs in the assumptions about

- [ The intercept
- [ The slope coefficients

## Fixed Effects Models with Dummy Variables

	Varies over individuals	Varies over time
The intercept	✓	—
The slope coefficients	—	—

Different intercepts for different individuals  $\beta_{1i}$

$$Y_{it} = \beta_{1i} + \beta_2 X_{2it} + \beta_3 X_{3it} + u_{it}$$

but each individuals intercept does not vary over time

If the number of individuals is  $N = 4$

$$Y_{it} = \alpha_1 + \alpha_2 D_{2i} + \alpha_3 D_{3i} + \alpha_4 D_{4i} + \beta_2 X_{2it} + \beta_3 X_{3it} + u_{it}$$

## Fixed Effects Models with Dummy Variables

	Varies over individuals	Varies over time
The intercept	—	✓
The slope coefficients	—	—

Different intercepts for different time periods instead  $\beta_{1t}$

$$Y_{it} = \beta_{1t} + \beta_2 X_{2it} + \beta_3 X_{3it} + u_{it}$$

If the number of time periods is  $T = 20$

$$Y_{it} = \lambda_1 + \lambda_2 D_{2t} + \lambda_3 D_{3t} + \dots + \lambda_{20} D_{20t} + \beta_2 X_{2it} + \beta_3 X_{3it} + u_{it}$$

## Fixed Effects Models with Dummy Variables

	Varies over individuals	Varies over time
The intercept	✓	✓
The slope coefficients	—	—

Different intercepts for different individuals AND time periods  $\beta_{1it}$

$$Y_{it} = \beta_{1it} + \beta_2 X_{2it} + \beta_3 X_{3it} + u_{it}$$

For  $N = 4$  and  $T = 20$

$$Y_{it} = \alpha_1 + \alpha_2 D_{2i} + \alpha_3 D_{3i} + \alpha_4 D_{4i} + \lambda_1 + \lambda_2 D_{2t} + \lambda_3 D_{3t} + \dots + \lambda_{20} D_{20t} + \beta_2 X_{2it} + \beta_3 X_{3it} + u_{it}$$

## Fixed Effects Models with Dummy Variables

	Varies over individuals	Varies over time
The intercept	✓	—
The slope coefficients	✓	—

Both intercepts and slopes varies over individuals, introduces a lot of dummy variables

$$\begin{aligned}Y_{it} = & \alpha_1 + \alpha_2 D_{2i} + \alpha_3 D_{3i} + \alpha_4 D_{4i} + \beta_2 X_{2it} + \beta_3 X_{3it} \\& + \gamma_1 D_{2i} X_{2it} + \gamma_2 D_{2i} X_{3it} + \gamma_3 D_{3i} X_{2it} + \gamma_4 D_{3i} X_{3it} \\& + \gamma_5 D_{4i} X_{2it} + \gamma_6 D_{4i} X_{3it} + u_{it}\end{aligned}$$

the number of interaction terms is number of dummy variables  $\times$  number of explanatory variables

# Fixed Effects Models with Dummy Variables

Both intercepts and slopes varies over individuals and time  
requires even more variables



# Fixed Effects Models

## Cautions

- a lot of dummy variables
  - ⇒ less df
  - ⇒ increased risk of multicollinearity
- have to reflect on the assumptions about the error term  $u_{it}$ 
  - heteroscedasticity?
  - autocorrelation?

easily gets complicated when both time and space dimensions

## Random Effects Models

Now, in the Random Effects Model

$$Y_{it} = \beta_{1i} + \beta_2 X_{2it} + \beta_3 X_{3it} + u_{it}$$

the intercepts/effects  $\beta_{1i}$  are assumed to be random variables with mean value

$$E(\beta_{1i}) = \beta_1$$

and the intercept value for individual  $i$  can be expressed as

$$\beta_{1i} = \beta_1 + \varepsilon_i \quad i = 1, \dots, N$$

where  $E(\varepsilon_i) = 0$  and  $Var(\varepsilon_i) = \sigma_\varepsilon^2$

## Random Effects Models

each individual in the sample is considered to be a drawing from an infinite (or "close to") population of individuals which share the common mean value  $\beta_1$

$$Y_{it} = \beta_1 + \beta_2 X_{2it} + \beta_3 X_{3it} + \varepsilon_i + u_{it}$$

$$Y_{it} = \beta_1 + \beta_2 X_{2it} + \beta_3 X_{3it} + w_{it}$$

The error term  $w_{it}$  consists of two components, random effects models are sometimes called error components models

## Random Effects Models

Assumptions about the error components

$$\left. \begin{aligned} \varepsilon_i &\sim N(0, \sigma_\varepsilon^2) \\ E(\varepsilon_i \varepsilon_j) &= 0 \quad \text{for } i \neq j \\ u_{it} &\sim N(0, \sigma_u^2) \\ E(u_{it} u_{is}) &= E(u_{it} u_{it}) = E(u_{it} u_{js}) = 0 \quad \text{for } i \neq j \text{ } t \neq s \\ E(\varepsilon_i u_{it}) &= 0 \end{aligned} \right\}$$

## Random Effects Models

$$\Rightarrow \left\{ \begin{array}{l} E(w_{it}) = 0 \\ Var(w_{it}) = \sigma_{\varepsilon}^2 + \sigma_u^2 \\ Corr(w_{it}, w_{is}) = \frac{\sigma_{\varepsilon}^2}{\sigma_{\varepsilon}^2 + \sigma_u^2} \end{array} \right.$$

## Random Effects vs Fixed Effects

depends on

- whether or not the individuals can be viewed as a random sample from a large population

- 

$$E(\varepsilon_i X_i) = 0?$$

If yes: random effects, if no: fixed effects

- the relation between  $T$  and  $N$ 
  - for large  $T$  and small  $N$  not a big difference
  - for small  $T$  and large  $N$  random effects estimators are more efficient than fixed effects (if the assumptions hold)