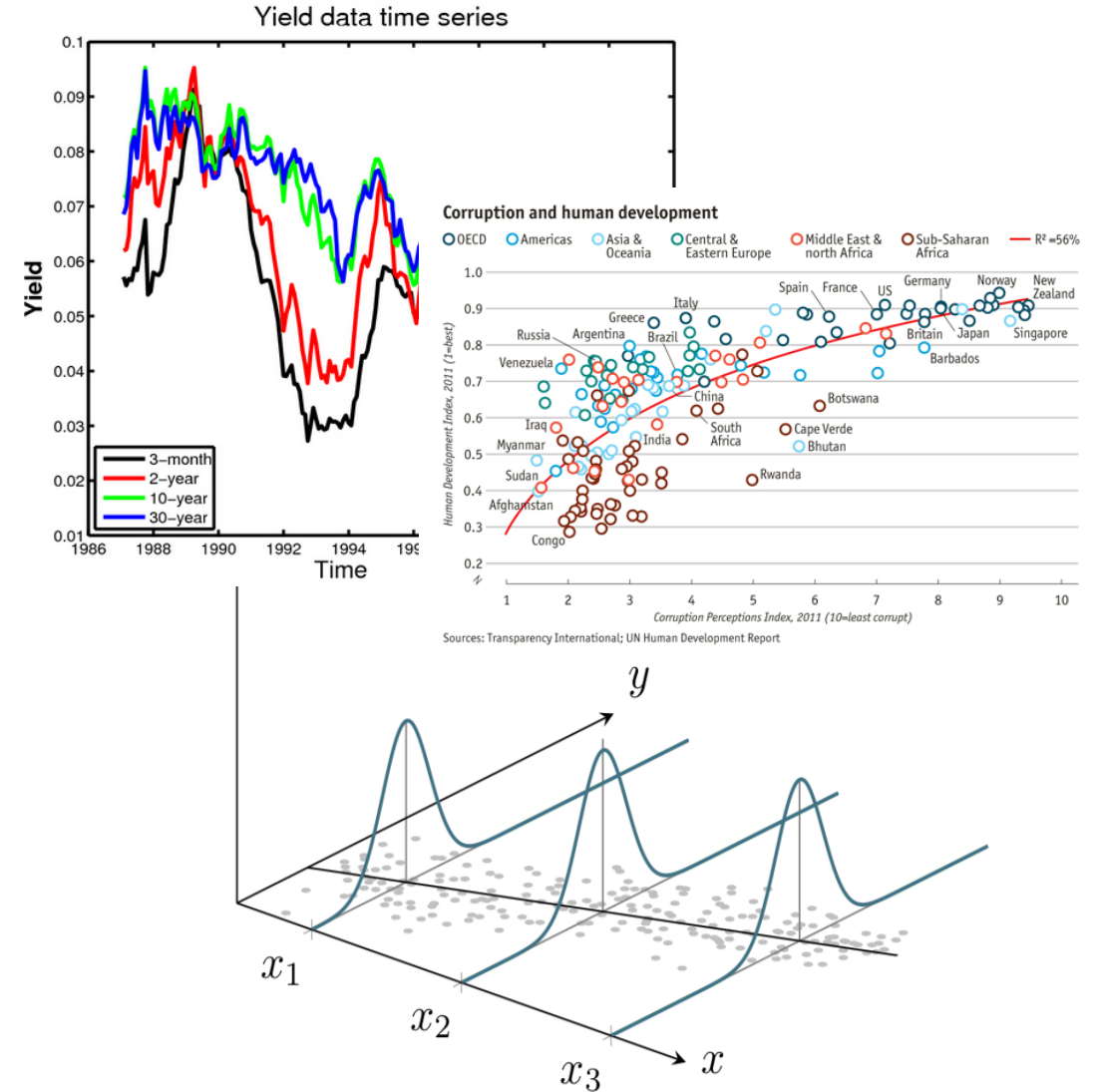


# Chapter 14

## Advanced Panel Data Methods



# Advanced Panel Data Methods (1 of 15)

- **Fixed effects estimation**

$$y_{it} = \beta_1 x_{it1} + \dots + \beta_k x_{itk} + a_i + u_{it}, \quad i = 1, \dots, N, t = 1, \dots, T$$

Fixed effect, potentially correlated  
with explanatory variables

$$\bar{y}_i = \beta_1 \bar{x}_{i1} + \dots + \beta_k \bar{x}_{ik} + \bar{a}_i + \bar{u}_i$$

Form time-averages  
for each individual

$$\Rightarrow [y_{it} - \bar{y}_i] = \beta_1 [x_{it1} - \bar{x}_{i1}] + \dots + \beta_k [x_{itk} - \bar{x}_{ik}] + [u_{it} - \bar{u}_i]$$

Because  $a_i - \bar{a}_i = 0$  (the fixed effect is removed)

- Estimate time-demeaned equation by OLS
  - Uses time variation within cross-sectional units (= within estimator)

# Advanced Panel Data Methods (2 of 15)

- **Example: Effect of training grants on firm scrap rate**

$$scrap_{it} = \beta_1 d88_{it} + \beta_2 d89_{it} + \beta_3 grant_{it} + \beta_4 grant_{it-1} + a_i + u_{it}$$

Time-invariant reasons why one firm is more productive than another are controlled for.  
The important point is that these may be correlated with the other explanatory variables.

- Fixed-effects estimation using the years 1987, 1988, and 1989:

$$\widehat{scrap}_{it}^* = - .080 \underset{(.109)}{d88_{it}^*} - .247 \underset{(.133)}{d89_{it}^*} - .252 \underset{(.151)}{grant_{it}^*} - .422 \underset{(.210)}{grant_{it-1}^*}$$

Stars denote time-demeaning

$$n = 162, R^2 = .201$$

Training grants significantly improve productivity (with a time lag)

# Advanced Panel Data Methods (3 of 15)

- **Discussion of fixed effects estimator**

- Strict exogeneity in the original model has to be assumed.
- The R-squared of the demeaned equation is inappropriate.
- The effect of time-invariant variables cannot be estimated.
- The effect of interactions with time-invariant variables can be estimated (e.g. the interaction of education with time dummies).
- If a full set of time dummies are included, the effect of variables whose change over time is constant cannot be estimated (e.g. experience).
- Degrees of freedom have to be adjusted because the  $N$  time averages are estimated in addition (resulting degrees of freedom =  $NT - N - k$ ).

# Advanced Panel Data Methods (4 of 15)

- **Interpretation of fixed effects as dummy variable regression**

- The fixed effects estimator is equivalent to introducing a dummy for each individual in the original regression and using pooled OLS:

$$y_{it} = a_1 ind1_{it} + a_2 ind2_{it} + \dots + a_N indN_{it} \leftarrow \text{For example, } = 1 \text{ if the observation stems from individual } N, = 0 \text{ otherwise}$$
$$+ \beta_1 x_{it1} + \dots + \beta_k x_{itk} + u_{it}$$

- After fixed effects estimation, the fixed effects can be estimated as:

$$\hat{a}_i = \bar{y}_i - \hat{\beta}_1 \bar{x}_{i1} - \dots - \hat{\beta}_k \bar{x}_{ik}, \quad i = 1, \dots, N \leftarrow \text{Estimated individual effect for individual } i$$

# Advanced Panel Data Methods (5 of 15)

- **Fixed effects or first differencing?**

- Remember that first differencing can also be used if  $T > 2$ .
- In the case  $T = 2$ , fixed effects and first differencing are identical.
- For  $T > 2$ , fixed effects is more efficient if classical assumptions hold.
- First differencing may be better in the case of severe serial correlation in the errors, for example if the errors follow a random walk.
- If  $T$  is very large (and  $N$  not so large), the panel has a pronounced time series character and problems such as strong dependence arise.
- In these cases, it is probably better to use first differencing.
- Otherwise, it is a good idea to compute both and check robustness.

# Advanced Panel Data Methods (6 of 15)

- **Unbalanced panels**

- An unbalanced panel is when not all cross-sectional units have the same number of observations.
  - Dropping units with only one time period does not cause bias or inconsistency.

- **Fixed effects (FE) or First Differencing (FD) with unbalanced panels**

- FE will preserve more data than FD when we have unbalanced panels, since FD requires that each observation have data available for both  $t$  and  $t-1$ .
- For example, consider a scenario in which we have seven years of data, but data is missing for all even numbered years. Thus, we observe  $t=1,3,5,7$ .
  - FE will use time periods 1,3,5,7
  - FD will lose all observations.

# Advanced Panel Data Methods (7 of 15)

- **Random effects (RE) models**

$$y_{it} = \beta_0 + \beta_1 x_{it1} + \dots + \beta_k x_{itk} + a_i + u_{it}$$

← The individual effect is assumed to be “random”  
i.e. completely unrelated to explanatory variables

Random effects assumption:  $Cov(x_{itj}, a_i) = 0, j = 1, 2, \dots, k$

- The composite error  $a_i + u_{it}$  is uncorrelated with the explanatory variables but it is serially correlated for observations coming from the same  $i$ :

$$Cov(a_i + u_{it}, a_i + u_{is}) = Cov(a_i, a_i) = \sigma_a^2$$

← Under the assumption that  
idiosyncratic errors are  
serially uncorrelated

For example, in a wage equation, for a given individual the same unobserved ability appears in the error term of each period. Error terms are thus correlated across periods for this individual.



# Advanced Panel Data Methods (8 of 15)

- **Estimation in the random effects model**

- Under the random effects assumptions explanatory variables are exogenous so that pooled OLS provides consistent estimates.
- If OLS is used, standard errors have to be adjusted for the fact that errors are correlated over time for given  $i$  (= clustered standard errors).
- But, because of the serial correlation, OLS is not efficient.
- One can transform the model so that it satisfies the GM-assumptions:

$$[y_{it} - \lambda \bar{y}_i] = \beta_1 [x_{it1} - \lambda \bar{x}_{i1}] + \dots + \beta_k [x_{itk} - \lambda \bar{x}_{ik}] \leftarrow \text{Quasi-demeaned data}$$
$$+ [a_i - \lambda \bar{a}_i + u_{it} - \lambda \bar{u}_i] \leftarrow \text{Error can be shown to satisfy GM-assumptions}$$

## Advanced Panel Data Methods (9 of 15)

- **Estimation in the random effects model (cont.)**


$$\lambda = 1 - \left[ \sigma_u^2 / (\sigma_u^2 + T\sigma_a^2) \right]^{1/2}, \quad 0 \leq \lambda \leq 1$$

- The quasi-demeaning parameter is unknown but it can be estimated.
- FGLS using the estimated  $\lambda$  is called random effects estimation.
- If the random effect is relatively unimportant compared to the idiosyncratic error, FGLS will be close to pooled OLS (because  $\lambda$  goes to 0).
- If the random effect is relatively important compared to the idiosyncratic term, FGLS will be similar to fixed effects (because  $\lambda$  goes to 1).
- Random effects estimation can be used to estimate the effect of time-invariant variables.

# Advanced Panel Data Methods (10 of 15)

- **Example: Wage equation using panel data**

$$\begin{aligned}\widehat{\log(wage_{it})} = & \underset{(.011)}{.092} educ_{it} - \underset{(.048)}{.139} black_{it} + \underset{(.043)}{.022} hispan_{it} \\ & + \underset{(.015)}{.106} exper_{it} - \underset{(.0007)}{.0047} exper_{it}^2 + \underset{(.017)}{.064} married_{it} \\ & + \underset{(.018)}{.106} union_{it} + time\ dummies\end{aligned}$$



Random effects is used because many of the variables are time-invariant. But is the random effects assumption realistic?

- **Random effects or fixed effects?**

- In economics, unobserved individual effects are seldomly uncorrelated with explanatory variables so that fixed effects is more convincing.

# Advanced Panel Data Methods (11 of 15)

- **Correlated Random Effects (CRE)**

- When using CRE to choose between FE and RE, we must include any time-constant variables that appear in RE estimation:

$$y_{it} = \alpha_1 + \alpha_2 d2_t + \dots + \alpha_T dT_t + \beta_1 x_{it1} + \dots + \beta_k x_{itk} \\ + \gamma_1 \bar{x}_{i1} + \dots + \gamma_k \bar{x}_{ik} + \delta_1 z_{i1} + \dots + \delta_m z_{im} + r_i + u_{it}$$

- Estimating this equation by RE (or even just pooled OLS) yields:

$$\hat{\beta}_{CRE,j} = \hat{\beta}_{FE,j}; j = 1, \dots, k \quad \leftarrow \text{Time varying estimates will be the same as in FE}$$
$$\hat{\alpha}_{CRE,t} = \hat{\alpha}_{FE,t}; t = 1, \dots, T$$

$$H_0: \gamma_1 = \gamma_2 = \dots = \gamma_k = 0 \quad \leftarrow \text{Under the null, RE is sufficient. If we reject the null, then FE is preferred.}$$

- An advantage of CRE is that it allows for estimation of the effects of time-constant explanatory variables, not possible using FE.

## Advanced Panel Data Methods (12 of 15)

- **General policy analysis with panel data**

- The two-period, before-after setting is a special case of a more general policy analysis framework when  $T \geq 2$ .

$$y_{it} = \eta_1 + \alpha_2 d2_t + \cdots + \alpha_T dT_t + \beta w_{it} + \mathbf{x}_{it}\boldsymbol{\psi} + a_i + u_{it}$$

$w_{it}$  is the binary policy variable and  $\beta$  estimates the average treatment effect of the policy

- To allow  $w_{it}$  to be systematically related to the unobserved fixed effect  $a_i$ , we estimate the regression with either FD or FE, using cluster-robust standard errors.
- We can also include lags of the policy intervention:  $w_{it-1}, w_{it-2}, \dots$

## Advanced Panel Data Methods (13 of 15)

- **Testing for feedback from the error term to the policy variable**
- We need to be careful if the policy variable  $w_{it}$  it reacts to past shocks.
  - Example:  $y_{it}$  is the poverty rate and  $w_{it}$  is some measure of government assistance.
  - A large shock to the poverty rate in year  $t$  could prompt an increase in government assistance the following year.

- If we have at least three time periods, we can test for feedback

$$y_{it} = \eta_1 + \alpha_2 d2_t + \dots + \alpha_{T-1} dT - 1_t + \beta w_{it} + \delta w_{it+1} + x_{it} \psi + a_i + u_{it}$$

← Estimate with FE and compute a cluster robust t-statistic for  $\hat{\delta}$

- This is known as a “falsification test.”
  - If the forward policy variable is statistically significant, there is potential feedback from the error term to the policy variable.

## Advanced Panel Data Methods (14 of 15)

- **The heterogeneous trend model**
- What if time trends are unique across individuals?

$$y_{it} = \eta_1 + \alpha_2 d2_t + \dots + \alpha_T dT_t + \beta w_{it} + \mathbf{x}_{it}\boldsymbol{\psi} + a_i + g_i t + u_{it}$$

The new term  $g_i t$  is a unit-specific time trend.

- This allows the policy intervention to not only be correlated with level differences among units (captured by  $a_i$ ), but also by trend differences.
- We can estimate this model by taking first differences:

$$\Delta y_{it} = \alpha_2 \Delta d2_t + \dots + \alpha_T \Delta dT_t + \beta \Delta w_{it} + \Delta \mathbf{x}_{it}\boldsymbol{\psi} + g_i + \Delta u_{it}$$

Estimate by FE., though we need to ensure we have  $T \geq 3$

# Advanced Panel Data Methods (15 of 15)

- **Applying panel data methods to other data structures**

- Panel data methods can be used in other contexts where constant unobserved effects have to be removed.
- Example: Wage equations for twins

Unobserved genetic and family characteristics that do not vary across twins

$$\log(wage_{i1}) = \beta_0 + \beta_1 educ_{i1} + \dots + a_i + u_{i1} \leftarrow \text{Equation for twin 1 in family } i$$

$$\log(wage_{i2}) = \beta_0 + \beta_1 educ_{i2} + \dots + a_i + u_{i2} \leftarrow \text{Equation for twin 2 in family } i$$

$$\Rightarrow \Delta \log(wage_i) = \beta_1 \Delta educ_i + \dots + \Delta u_i \leftarrow \text{Estimate differenced equation by OLS}$$