Outline

1. Course outline

2. Panel data
   - Advantages of Panel Data
   - Limitations of Panel Data

3. Pooled OLS estimator

4. Fixed effects model
   - The Least Squares Dummy Variable Estimator
   - The Fixed Effect (Within Group) Estimator
Literature

Basic:

Additional:
Topics

1. Panel data - basic definitions, characteristics, etc.
2. Linear static model - common types. Fixed and random effects approaches.
3. Fixed effects estimation.
4. Random effects estimation.
5. Verification and forecasting with the use of linear static models.
7. Problem of missing observations, applications of Hausman’s test.
8. IV and GIVE estimators in the estimation of static panel data models.
9. The use of IV and GIVE - developed HT method, endogeneity of variables.
10. Estimation of dynamic models - estimator of Arellano and Bond.
11. Limited dependent variables and panel data.
13. RE probit and FE logit models: estimation, verification, inference.
14. Spatial panel data.
15. Nonstationary panels.
Office hours: TBA.

E-mail: jakub.muck@gmail.com.

WWW: http://akson.sgh.waw.pl/jm39985/
  ➞ english
  ➞ teaching
  ➞ Econometrics of Panel Data.

Software: Stata (+ R).

Exam rules:
  ▶ Exam: 60 %.
  ▶ Classes: 40% – houseworks and activity.
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Panel data

Panel of data consists of a group of cross-section units (people, firms, states, countries) that are observed over the time:

- **Cross-section:**
  \[ y_i \text{ where} \]
  \[ i \in \{1, \ldots, N\}. \]

- **Time series:**
  \[ y_t \text{ where} \]
  \[ t \in \{1, \ldots, T\}. \]

- **Panel data:**
  \[ y_{it} \text{ where} \]
  \[ i \in \{1, \ldots, N\} \]
  \[ t \in \{1, \ldots, T\}. \]

In general,

- **\( N \)** - the cross-sectional dimension.
- **\( T \)** - the time dimension.
Panel data

We might describe panel data using $T$ and $N$:

- **long/short** describes the time dimension ($T$);
- **wide/narrow** describes the cross-section dimension ($N$);

*For example: panel with relatively large $N$ and $T$: long and wide panel.*
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For example: panel with relatively large $N$ and $T$: long and wide panel.

- **In a balanced** panel, each individuals(unit) has the same number of observation.
- **Unbalanced** panel is a panel in which the number of time series observations is different across units.
Examples of panel data

Micro data

- PSID – the Panel Study of Income Dynamics collected by the Institute for Social Research at the University of Michigan.
- NLS – the National Longitudinal Surveys collected by the Bureau of Labor Statistics.
- CPS – Current Population Survey conducted by the Bureau of Census (monthly frequency).

Macro data

- Penn World Table,
- WDI Indicators.

Sectoral data

- KLEMS database.
Advantages of Panel Data (Baltagi, 2014)

- Controlling for **individual heterogeneity**.
- Panel data offer more informative data, more variability, less collinearity among the dependent variables, more degrees of freedom and more efficiency in estimation.
- Identification and measurement of effects that are simply not detectable in pure cross-section or pure time-series data.
- Testing more complicated behavioral models than purely cross-section or time-series data.
- Reduction in biases resulting from aggregation over firms or individuals.
- Overcome the problem of nonstandard distributions typical of unit roots tests \(\Rightarrow\) macro panels.
Limitations of Panel Data

- Design and data collection problems:
  - coverage;
  - nonresponse;
  - frequency of interviewing;

- Distortions of measurement errors

- Selectivity problems:
  - self-selectivity;
  - nonresponse;
  - attrition;

- Short $T$.

- Cross-sectional dependence.
Two examples (Arellano, 2003)

Classical example

**Agricultural Cobb-Douglas production function.** Consider the following model:

\[ y_{it} = \beta x_{it} + u_{it} + \eta_i \]  

- \( y_{it} \) – the log output.
- \( x_{it} \) – the log of a variable output;
- \( \eta_i \) – an farm-specific input that is constant over time, e.g., soil quality.
- \( u_{it} \) – a stochastic input that is outside framer’s control, e.g., rainfalls.
- \( \beta \) - the technological parameter.

An example in which panel data does not work

**Returns to education.** Consider the following model:

\[ y_{it} = \alpha + \beta x_{it} + u_{it} \]  

- \( y_{it} \) – the log wage;
- \( x_{it} \) – years of the full-time education;
- \( \beta \) – returns to education.

In addition:

\[ u_{it} = \eta_i + \epsilon_{it} \]  

where \( \eta_i \) stands for the unobserved individual ability.

Problem:

\( x_{it} \) lacks of time variation.
Two examples (Arellano, 2003)

- **Classical example**

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- **An example in which panel data does not work**

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Pooled OLS estimator

- **Pooled model** is one where the data on different units are pooled together with **no assumption on individual differences**:

\[ y_{it} = \alpha + \beta_1 x_{1it} + \ldots + \beta_k x_{kit} + u_{it} \]  

(4)

where

- \( y_{it} \) – the dependent variable;
- \( x_{kit} \) – the \( k \)th explanatory variable;
- \( u_{it} \) – the error/disturbance term;
- \( \alpha \) – the intercept;
- \( \beta_1, \ldots, \beta_k \) – the structural parameters;

- Note that the coefficients \( \alpha, \beta_1, \ldots, \beta_k \) are the same for all unit (don’t have \( i \) or \( t \) subscript).
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Note that the coefficients \( \alpha, \beta_1, \ldots, \beta_k \) are the same for all unit (don’t have \( i \) or \( t \) subscript).
Pooled OLS estimator

- In vector form:

\[ y = X\beta + u \]  \hfill (5)

where \( y \) is \( NT \times 1 \), \( \beta \) is \( (K + 1) \times 1 \), \( X \) is \( NT \times K \) and \( u \) is \( NT \times 1 \) and:

\[
X = \begin{bmatrix}
1 & x_{11} & \ldots & x_{k1} \\
1 & x_{12} & \ldots & x_{k2} \\
\vdots & \vdots & \ddots & \vdots \\
1 & x_{1N} & \ldots & x_{kN}
\end{bmatrix}
\quad \text{and} \quad
y = \begin{bmatrix}
y_1 \\
y_2 \\
\vdots \\
y_N
\end{bmatrix}
\quad \text{and} \quad
\beta = \begin{bmatrix}
\alpha \\
\beta_1 \\
\vdots \\
\beta_K
\end{bmatrix}
\]

where \( x_{ij} \) is the vector of observations of the \( j \)th independent variable for unit \( i \) over the time and \( y_i \) is the vector of observation of the explained variable for unit \( i \).

- Then:

\[
\hat{\beta}^{POOLED} = (X'X)^{-1} X'y = \begin{bmatrix}
\hat{\alpha}^{POOLED} \\
\hat{\beta}_1^{POOLED} \\
\vdots \\
\hat{\beta}_K^{POOLED}
\end{bmatrix}
\]  \hfill (6)
Pooled OLS estimator

Assumptions (for linear pooled model):

\[ E(u) = 0 \]  
\[ E(uu') = \sigma^2_u I \]
\[ \text{rank}(X) = K + 1 < NT \]
\[ E(u|X) = 0 \]

- (10): X is nonstochastic and is not correlated with u.
- (8): the error term (u) is not autocorrelated and homoscedastic.
- (10) \(\implies\) strictly exogeneity of independent variables.

Gauss-Markov Theorem

If (7)-(10) and are satisfied then \(\hat{\beta}^{POOLED}\) is BLUE (the best linear unbiased estimator).
Empirical example

Grunfeld’s (1956) investment model:

\[ I_{it} = \alpha + \beta_1 K_{it} + \beta_2 F_{it} + u_{it} \]  \hspace{1cm} (11)

where

- \( I_{it} \) – the gross investment for firm \( i \) in year \( t \);
- \( K_{it} \) – the real value of the capital stocked owned by firm \( i \);
- \( F_{it} \) – is the real value of the firm (shares outstanding).

The dataset consists of 10 large US manufacturing firms over 20 years (1935–54).
Empirical example

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<thead>
<tr>
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<tbody>
<tr>
<td>$\alpha$</td>
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**Note:** The expressions in round and squared brackets stand for standard errors and probability values corresponding to the null about parameter’s insignificance, respectively.

$$I_{it} = \alpha + \beta_1 K_{it} + \beta_2 F_{it} + u_{it}$$
The general assumption in pooled regression on the error terms are very strong or even unrealistic.

The lack of correlation between errors corresponding to the same individuals.

Let’s relax the above assumption:

\[
\text{cov}(u_{i,t}, u_{i,s}) \neq 0
\]  (12)

Then we have problem of both autocorrelation and heteroskedasticity.

The OLS estimator is still consistent but the standard errors are incorrect.

We might use the \textit{clustered/robust standard errors}. Here, the time series for each individual are clusters.
Standard errors

- If the assumptions (7)-(10) are satisfied then the variance-covariance matrix of $\beta$ is equal to:
  \[ \text{Var}(\beta) = \sigma^2 (X'X)^{-1} = D \]  
  \[ \text{(13)} \]
  where $\sigma^2$ is the variance of the error term.

- The standard errors stand for the diagonal elements:
  \[ \text{s.e.}(\beta_i) = \sqrt{D_{ii}} \]  
  \[ \text{(14)} \]

- One step back in (13):
  \[ \text{Var}(\beta) = (X'X)^{-1} X' \Sigma X (X'X)^{-1} \]  
  \[ \text{(15)} \]
  (15) simplifies to (13) when $\text{Var}(u) = \sigma^2 I$.

- But when we don’t know $\Sigma$?

- White’s (1980) heteroscedasticity-consistent estimator of the variance-covariance matrix:
  \[ \Sigma = \text{diag}(\hat{u}_1^2, \hat{u}_2^2, \ldots, \hat{u}_N^2) \]  
  \[ \text{(16)} \]
  where $\hat{u}$ is the vector of residuals.
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\[ I_{it} = \alpha + \beta_1 K_{it} + \beta_2 F_{it} + u_{it} \]
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One-way Error Component Model

In the model:

\[ y_{it} = \alpha + X'_{it} \beta + u_{it} \quad i \in \{1, \ldots, N\}, \ t \in \{1, \ldots, T\} \]  

(17)

it is assumed that all units are homogeneous. Why?

**One-way error component model:**

\[ u_{i,t} = \mu_i + \varepsilon_{i,t} \]  

(18)

where:

- \( \mu_i \) – the unobservable individual-specific effect;
- \( \varepsilon_{i,t} \) – the remainder disturbance.
Fixed effects model

- We can relax assumption that all individuals have the same coefficients

\[ y_{it} = \alpha_i + \beta_1 x_{1it} + \ldots + \beta_k x_{kit} + u_{it} \]  

(19)

- Note that an \(i\) subscript is added to only intercept \(\alpha_i\) but the slope coefficients, \(\beta_1, \ldots, \beta_k\) are constant for all individuals.

- **An individual intercept** (\(\alpha_i\)) are include to control for individual-specific and time-invariant characteristics. That intercepts are called **fixed effects**.

- Fixed effects capture the **individual heterogeneity**.

- The estimation:
  i) The least squares dummy variable estimator
  ii) The fixed effects estimator
The Least Squares Dummy Variable Estimator

- The natural way to estimate fixed effect for all individuals is to include an indicator variable. For example, for the first unit:

\[ D_{1i} = \begin{cases} 
1 & i = 1 \\
0 & \text{otherwise} 
\end{cases} \] (20)

The number of dummy variables equals \( N \). It’s not feasible to use the least square dummy variable estimator when \( N \) is large.

- We might rewrite the fixed regression as follows:

\[ y_{it} = \sum_{j=1}^{N} \alpha_i D_{ji} + \beta_1 x_{1it} + \ldots + \beta_k x_{kit} + u_{i,t} \] (21)

- Why \( \alpha \) is missing?
The Least Squares Dummy Variable Estimator

In the matrix form:

\[ y = X\beta + u \]  \hspace{1cm} (22)

where \( y \) is \( NT \times 1 \), \( \beta \) is \( (K + N) \times 1 \), \( X \) is \( NT \times (K + N) \) and \( u \) is \( NT \times 1 \).

\[
X = \begin{bmatrix}
1 & 0 & \ldots & 0 & x_{11} & \ldots & x_{k1} \\
0 & 1 & \ldots & 0 & x_{12} & \ldots & x_{k2} \\
\vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\
0 & 0 & \ldots & 1 & x_{1N} & \ldots & x_{kN}
\end{bmatrix}
\]

and

\[
y = \begin{bmatrix}
y_1 \\
y_2 \\
\vdots \\
y_N
\end{bmatrix}
\]

and

\[
\beta = \begin{bmatrix}
\alpha_1 \\
\vdots \\
\alpha_N \\
\beta_1 \\
\vdots \\
\beta_K
\end{bmatrix}
\]

where \( x_{ij} \) is the vector of observations of the \( j \)th independent variable for unit \( i \) over the time and \( y_i \) is the vector of observation of the explained variable for unit \( i \).

Then:

\[
\hat{\beta}_{LSDV} = (X'X)^{-1} X'y = [\hat{\alpha}_1^{LSDV} \ldots \hat{\alpha}_N^{LSDV} \hat{\beta}_1^{LSDV} \ldots \hat{\beta}_K^{LSDV}]'
\]  \hspace{1cm} (23)
The Least Squares Dummy Variable Estimator

- We can test estimates of intercept to verify whether the fixed effects are different among units:

\[ \mathcal{H}_0 : \alpha_1 = \alpha_2 = \ldots = \alpha_N \quad (24) \]

- To test (24) we estimate: i) unrestricted model (the least squares dummy variable estimator) and ii) restricted model (pooled regression). Then we calculate sum of squared errors for both models: \( SSE_U \) and \( SSE_R \).

\[ F = \frac{(SSE_R - SSE_U)/(N - 1)}{SSE_U/(NT - K)} \quad (25) \]

if null is true then \( F \sim F_{(N-1, NT-K)} \).
The Fixed Effect (Within Group) Estimator

- Let’s start with simple fixed effects specification for individual $i$:

$$y_{it} = \alpha_i + \beta_1 x_{1it} + \ldots + \beta_k x_{kit} + u_{it} \quad t = 1, \ldots, T \quad (26)$$

- **Average the observation across time** and using the assumption on time-invariant parameters we get:

$$\bar{y}_i = \alpha_i + \beta_1 \bar{x}_{1i} + \ldots + \beta_k \bar{x}_{ki} + \bar{u}_i \quad (27)$$

where $\bar{y}_i = \frac{1}{T} \sum_{t=1}^{T} y_{it}$, $\bar{x}_{1i} = \frac{1}{T} \sum_{t=1}^{T} x_{1it}$, $\bar{x}_{ki} = \frac{1}{T} \sum_{t=1}^{T} x_{kit}$ and $\bar{u}_i = \frac{1}{T} \sum_{t=1}^{T} u_{it}$

- Now we subtract (27) from (26)

$$y_{it} - \bar{y}_i = (\alpha_i - \alpha_i) + \beta_1 (x_{1it} - \bar{x}_{1i}) + \ldots + \beta_k (x_{ikt} - \bar{x}_{ki}) + (u_{it} - \bar{u}_i) \quad (28)$$

Using notation: $\tilde{y}_{it} = (y_{it} - \bar{y}_i)$, $\tilde{x}_{1it} = (x_{1it} - \bar{x}_{1i})$, $\tilde{x}_{kit} = (x_{kit} - \bar{x}_{ki})$ $\tilde{u}_{it} = (u_{it} - \bar{u}_i)$, we get

$$\tilde{y}_{it} = \beta_1 \tilde{x}_{1it} + \ldots + \beta_k \tilde{x}_{kit} + \tilde{u}_{it} \quad (29)$$

Note that we **don’t estimate directly fixed effects**.
The Fixed Effect (Within Group) Estimator

- The Fixed Effect Estimator or the within (group) estimator in vector form:

\[ \tilde{y} = \tilde{X}\beta + \tilde{u} \quad (30) \]

where \( \tilde{y} \) is \( NT \times 1 \), \( \beta \) is \( K \times 1 \), \( \tilde{X} \) is \( NT \times K \) and \( \tilde{u} \) is \( NT \times 1 \) and:

\[ \tilde{X} = \begin{bmatrix} \tilde{x}_{11} & \ldots & \tilde{x}_{k1} \\ \tilde{x}_{12} & \ldots & \tilde{x}_{k2} \\ \vdots & \ddots & \vdots \\ \tilde{x}_{1N} & \ldots & \tilde{x}_{kN} \end{bmatrix} \quad \text{and} \quad \tilde{y} = \begin{bmatrix} \tilde{y}_1 \\ \tilde{y}_2 \\ \vdots \\ \tilde{y}_N \end{bmatrix} \quad \text{and} \quad \beta = \begin{bmatrix} \beta_1 \\ \vdots \\ \beta_K \end{bmatrix} \]

Then:

\[ \hat{\beta}^{FE} = (\tilde{X}'\tilde{X})^{-1}\tilde{X}'\tilde{y} = [\hat{\beta}_1^{FE} \ldots \hat{\beta}_K^{FE}]' \quad (31) \]

- The standard errors should be adjusted by using correction factor:

\[ \sqrt{\frac{NT - K}{NT - N - K}} \quad (32) \]

where \( K \) is number of estimated parameters without constant.

- The fixed effects estimates can be recovered by using the fact that OLS fitted regression passes the point of the means.

\[ \hat{\alpha}_i^{FE} = \bar{y}_i - \hat{\beta}_1^{FE}\bar{x}_{1i} - \hat{\beta}_2^{FE}\bar{x}_{2i} - \ldots - \hat{\beta}_k^{FE}\bar{x}_{ki} \quad (33) \]
Empirical example

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$$I_{it} = \alpha + \beta_1 K_{it} + \beta_2 F_{it} + u_{it}$$
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