Panel Data II

CS5056 Data Analytics

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What is Panel Data?

Panel data is a two-dimensional concept, where the same individuals are observed repeatedly over different periods in time

https://towardsdatascience.com/a-guide-to-panel-data-regression-theoretics-and-implementation-with-python-4c84c5055cf8

Panel Data

- In general, panel data can be seen as a combination of cross-sectional and time-series data
- Cross-sectional data is described as one observation of multiple individuals and corresponding variables at a specific point in time (i.e. an observation is taken once)
- Panel data comprises characteristics of both time and individuals into one model by collecting data from multiple, same individuals over time
- On the other hand, time-series data only observes one object recurrently over time

Key properties of a panel dataset:

property 1:

the same objects/individuals are observed repeatedly

property 2:

multiple variables are measured of those same individuals/objects

property 3:

the observations take place at multiple points in time

Panel Data Analysis

- A common panel data regression model looks like:

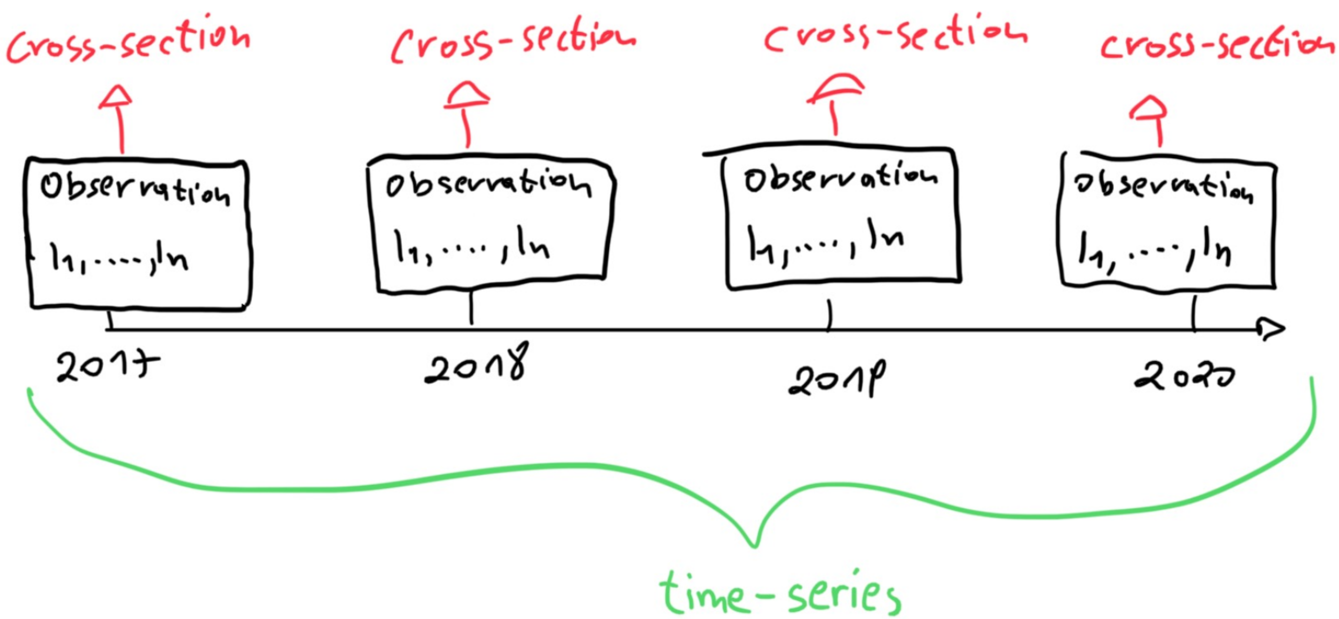
$$y_{it} = a_{it} + b_{it}x_{it} + e_{it}$$

- Where y is the dependent variable, x is the independent variable, a and b are coefficients, i and t are indices for individuals and time

- The term e_{it} represents the error

We can think of Panel Data like a timeline in which we **periodically observe the same individuals**

- https://towardsdatascience.com/a-guide-to-panel-data-regression-theoretics-and-implementation-with-python-4c84c5055cf8



Sample Panel Dataset

person	year	x	y
A	2018	3,5	85
A	2019	3,2	83
A	2020	3,8	88
B	2018	1,2	79
B	2019	1,5	83
B	2020	2,3	88
C	2018	5,6	75
C	2019	6	72
C	2020	5,8	78

Let´s say, we want to analyze the relationship on how coffee consumption affects the level of concentration. A simple linear regression model would look like this:

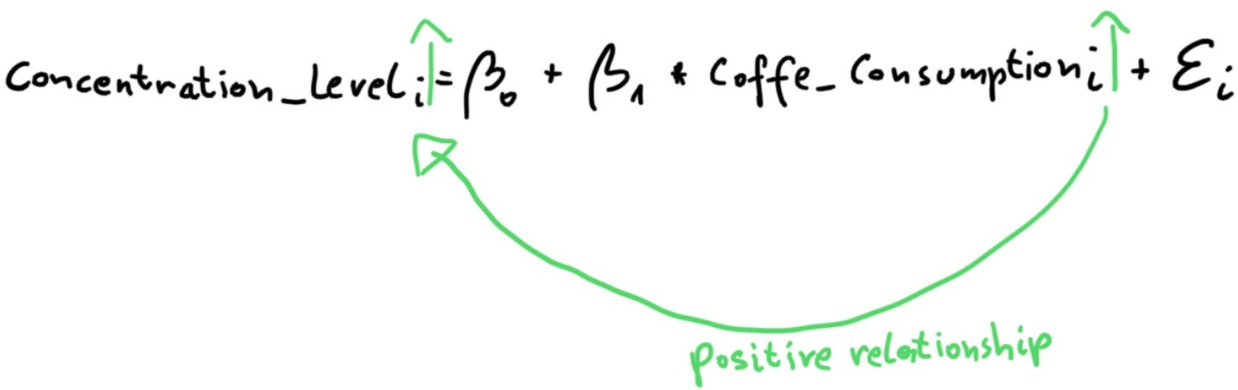
$$Concentration\_Level_i = \beta_0 + \beta_1 * Coffe\_Consumption_i + \varepsilon_i$$

Simple Linear Regression

where:

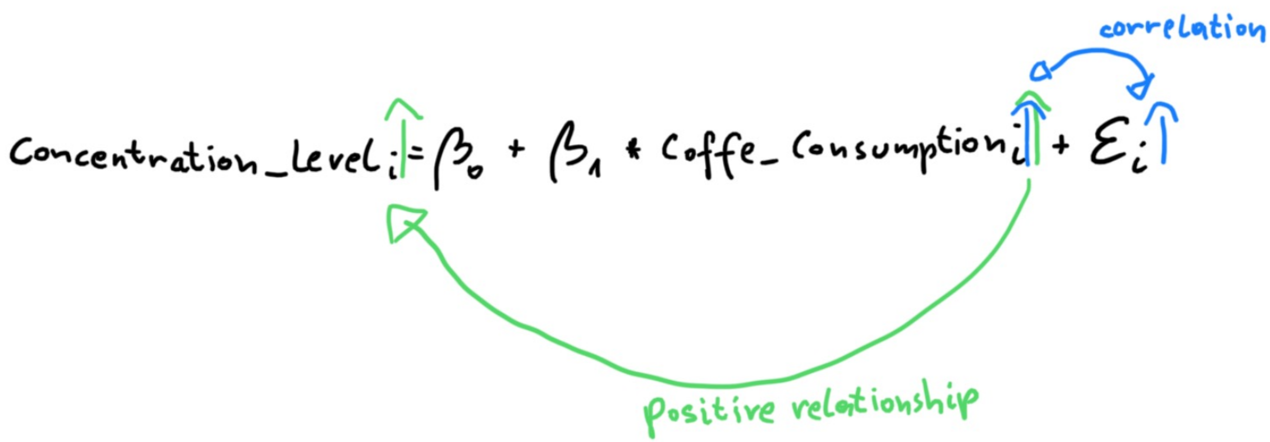
- *Concentration_Level is* the dependent variable (DV)
- *β0* is the intercept
- *β1* is the regression coefficient
- *Coffee_Consumption* is the independent variable (IV)
- ε is the error term

However, the goal of this model is to explore the relationship of *Coffee_Consumption* (IV) on the *Concentration_Level* (DV). Assuming that IV and DV are positively correlated, this would mean that if IV increases, DV would also increase. Let´s add this fact to our formula:



Relationship between IV and DV

But what, if there is another variabel that would affect existing IV(s) and is not included in the model? For example, *Tiredness* has a high chance to affect *Coffee_Consumption* (if you are tired, you will obviously drink coffee ;-)). If you remeber the first sentence of this article, such variables are called unobserved, independent variables. They are "hidden" behind the error term and if, e.g., *Coffee_Consumption* is positively related to such a variable, the error term would increase as *Coffee_Consumption* increases:



Correlation between IV and error term

Types of Panel Data Regression

The following explanations are built on this notation:

$$y_{it} = X_{it}\beta + \alpha_i + u_{it} \quad \text{for } t = 1, \dots, T \text{ and } i = 1, \dots, N$$

Notation

where:

- y = DV
- X = IV(s)
- β = Coefficients
- α = Individual Effects
- μ = Idiosyncratic Error

1) *PooledOLS:* *PooledOLS* can be described as simple OLS (Ordinary Least Squared) model that is performed on panel data. It ignores time and individual characteristics and focuses only on dependencies **between** the individuums. However, simple OLS requires that there is no correlation between unobserved, independent variable(s) and the IVs (i.e. exogeneity). Let´s write this down:

$$y_{it} = X_{it}\beta + \alpha_i + u_{it} \quad \text{for } t = 1, \ldots, T \text{ and } i = 1, \ldots, N$$

$$Cor(X_{it}, \alpha_i) = 0$$

Exogeneity Assumption

The problem with *PooledOLS* is that even the assumption above holds true, *alpha* might have a serial correlation over time. Consequentely, *PooledOLS* is mostly inappropriate for panel data.

$$Cov(\alpha_i, \alpha_j) = Var(\alpha_i) = \sigma_\alpha^2 > 0$$

Serial Correlation between alpha

Note: To counter this problem, there is another regression model called *FGLS* (Feasible Generalized Least Squares), which is also used in random effects models described below.

2) *Fixed-Effects (FE) Model:* The FE-model determines individual effects of unobserved, independent variables as constant ("fix") over time. Within FE-models, the relationship between unobserved, independent variables and the IVs (i.e. endogeneity) can be existent:

$$y_{it} = X_{it}\beta + \alpha_i + u_{it} \quad \text{for } t = 1, \dots, T \text{ and } i = 1, \dots, N$$

$$\mathrm{cov}(X_{it}, \alpha_i) \neq 0$$

Endogeneity allowed

The trick in a FE-model is, if we assume *alpha* as constant and subtract the mean values from each equation term, *alpha* (i.e. the unobserved heterogeneity) will get zero and can therefore be neglected:

$$y_{it} - \overline{y_i} = \beta(X_{it} - \overline{X_i}) + \underbrace{(\alpha_i - \overline{\alpha_i})}_{=0} + (u_{it} - \overline{u_i})$$

Solely, the idiosyncratic error (represented by *my* = unobserved factors that change over time and across units) remains and has to be exogen and non-collinear.

However, because heterogeneity can be controlled, this model allows heterogeneity to be existent within the model. Unfortunately, due to the fact that individual effects are fixed, dependencies can only be observed **within** the individuums.

Note: An alternative to the FE-model is the *LSDV*-model (Least Squares Dummy Variables), in which the (fixed) individual effects are represented by dummy variables. This model will lead to the exact same results, but has a main disadvantage, since it will need a lot more computation power if the regression model is big.

3) *Random-Effects (RE) Model:* RE-models determine individual effects of unobserved, independent variables as random variables over time. They are able to “switch” between OLS and FE and hence, can focus on both, dependencies **between** and **within individuals**. The idea behind RE-models is the following:

Let´s say, we have the same notation as above:

$$y_{it} = X_{it}\beta + \alpha_i + u_{it} \quad \text{for } t = 1, \dots, T \text{ and } i = 1, \dots, N$$

Notation

In order to include between- as well as within-estimators, we first need to define, when to use which estimator. In general, if the covariance between *alpha* and *IV(s)* is zero (or very small), there is no correlation between them and an OLS-model is preferred. If that covariance is not zero, there is a relationship that should be eliminated by using a FE-model:

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$$Cov(\alpha_i, X_{it}) \neq 0 \Rightarrow \text{FE-model}$$

$$Cov(\alpha_i, X_{it}) = 0 \Rightarrow \text{OLS}$$

When to use which model?

The problem with using OLS, as stated above, is the serial correlation between *alpha* over time. Hence, RE-models determine which model to take according to the serial correlation of the error terms. To do so, the model uses the term *lambda*. In short, *lambda* calculates how big the variance of *alpha* is. If it is zero, then there will be no variance of *alpha*, which, in turn, means that PooledOLS is the preferred choice. On the other side, if the variance of *alpha* tend to become very big, *lambda* tends to become one and therefore it might make sense to eliminate *alpha* and go with the FE-model.

$$\lambda = 1 - \left(\frac{\sigma_u^2}{\sigma_u^2 + T \cdot \sigma_\alpha^2} \right)$$

$\lambda = 0 \Rightarrow$ OLS

$\lambda = 1 \Rightarrow$ FE

Desicion-making Process

How to decide which Model is appropriate?

Choosing between PooledOLS and FE/RE: Basically, there are five assumptions for simple linear regression models that must be fulfilled. Two of them can help us in choosing between PooledOLS and FE/RE.

These assumptions are (1) Linearity, (2) Exogeneity, (3a) Homoskedasticity and (3b) Non-autocorrelation, (4) Independent variables are not Stochastic and (5) No Multicolinearity.

If assumption **(2)** or **(3)** (or both) are violated, then FE or RE might be more suitable.

Choosing between FE and RE: Answering this question depends on your assumption, if the individual, unobserved heterogeneity is a constant or random effect. But this question can also be answered perfoming the Hausman-Test.

Hausman-Test: In simple termns, the Hausman-Test is a test of endogeneity. By running the Hausman-Test, the null hypothesis is that the covariance between IV(s) and *alpha* is zero. If this is the case, then RE is preferred over FE. If the null hypothesis is not true, we must go with the FE-model.

So, we now understand the theoretics behind panel data regression. Let´s go to the fun stuff and build the model in Python step-by-step:

Problems with Panel Data

- **Endogeneity** refers to the relationship between the observed and unobserved variables, namely that they are dependent on one another.
- **Heterogeneity** refers to any difference between individuals.
- **Observed heterogeneity** usually consists of the covariates
- **Unobserved heterogeneity** consists of any unobserved difference not included in the model

Problems with Panel Data

- Unobserved heterogeneity is one possible cause of endogeneity
- Endogeneity is therefore the broader term
- Unobserved heterogeneity implies endogeneity but not the other way around.

Panel Data Assumptions

- Assumptions about the error term determine whether we speak of fixed effects or random effects
- In a fixed effects model, e_{it} is assumed ***to vary non-stochastically over i or t*** making the fixed effects model analogous to a ***dummy variable*** model in one dimension
- In a random effects model, e_{it} is assumed ***to vary stochastically over i or t*** requiring special treatment of the error variance matrix

Summary of Panel Data Methods

- Pooled OLS
- Fixed effects models
- Random effects models

Types of Panel Data Regression

$$y_{it} = X_{it}\beta + \alpha_i + u_{it} \quad \text{for } t = 1, \dots, T \text{ and } i = 1, \dots, N$$

- y = DV
- X = IV(s)
- β = Coefficients
- α = Individual Effects
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How to Decide which Model is Most Appropriate?

Choosing between PooledOLS and FE/RE: Basically, there are five assumptions for simple linear regression models that must be fulfilled. Two of them can help us in choosing between PooledOLS and FE/RE.

These assumptions are (1) Linearity, (2) Exogeneity, (3a) Homoskedasticity and (3b) Non-autocorrelation, (4) Independent variables are not Stochastic and (5) No Multicolinearity.

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Homoskedasticity

- Homoskedastic refers to a condition in which the variance of the residual, or error term, in a regression model is constant
- That is, the error term does not vary much as the value of the predictor variable changes
- The lack of homoskedasticity may suggest that the regression model may need to include additional predictor variables to explain the performance of the dependent variable.

How to Decide which Model is Most Appropriate?

Choosing between FE and RE: Answering this question depends on your assumption, if the individual, unobserved heterogeneity is a constant or random effect. But this question can also be answered perfoming the Hausman-Test.

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Speed Tickets Example

- The dataset contains 4 observations of two (imaginary) US counties— Crow County and Bull county (property 1).
- For each county, 2 variables were measured — the number of speed cameras installed and the number of traffic violations (property 2).
- And finally, measurements took place in 2 different discrete time points — 2018 and 2019 (property 3).

county	year	traffic_violation	speed_camera
crow county	2018	50	10
crow county	2019	20	30
bull county	2018	48	15
bull county	2019	35	25

https://towardsdatascience.com/panel-data-regression-a-powerful-time-series-modeling-technique-7509ce043fa8

> ***Does number of installed speed cameras impact number of traffic violation cases?***

If we run a simple linear OLS regression we should be able to quickly check the association — if there is any — between the two variables:

traffic_violation = f(speed_camera)

However, remember that this is no ordinary dataset, it’s a panel data. Which means we can use it far effectively than running a simple OLS regression.

How?

Speed Tickets Example

- We shouldn't forget that the independent variable has two other properties — county and year

- This means that there is a variation along individual and time dimensions, which we can capture in more advanced models that we are calling ***panel data regression***

a) Pooled OLS model

Pooled OLS (Ordinary Least Square) model treats a dataset like any other cross-sectional data and ignores that the data has a time and individual dimensions. That is why the assumptions are similar to that of ordinary linear regression.

$$TrafficViolation_{it} = b_0 + b_1\, SpeedCamera_{it} + u_{it}$$

b) Fixed effects model

While speed camera installation might have an impact on traffic violations, it is also possible that each individual county is different in terms of traffic violation because of reasons other than speed camera (e.g. higher rate of highway patrol?). However, this is not reflected in the above OLS model. Fixed effects models go a step further by taking into account the differences between individual entities (counties in our case):

$$TrafficViolation_{it} = b_1\, SpeedCamera_{it} + CountyFixedEffects + u_{it}$$

c) Random effects model

In fixed effects model we have controlled for differences between individual counties. But what about variables that are constant across individuals but change over time? A random effects model takes into consideration these individual variations *as well as* time dependent variations. The model eliminates biases from variables that are unobserved and change over time.

$$TrafficViolation_{it} = b_1\, SpeedCamera_{it} + CountyFixedEffects + YearFixedEffects + u_{it}$$

Modeling using OLS Panel Data

- How to fit the best model that shows the relationship between employee salary and his experience, projects undertaken and number of years of education?

- Panel Data modeling in R is done by the plm (Panel Linear Model) package

  - Let us try first Ordinary Linear Square (OLS) Pooled Panel Data

A Panel Data Case

A	B	C	D	E	F	G
log_sal	emp_id	time	experience	projects	educ	
5.56198	1	1	3	32	9	
5.72413	1	2	4	43	9	
4.76142	1	3	5	40	9	
5.96414	1	4	6	39	9	
6.09112	1	5	7	42	9	
6.98123	1	6	8	35	9	
6.54286	1	7	9	32	9	
6.94276	2	1	30	34	11	
6.18599	2	2	31	27	11	
6.71945	2	3	32	33	11	
6.2456	2	4	33	30	11	

```
> pool<-plm(dep~indep,data=d,model="pooling")
> summary(pool)
Oneway (individual) effect Pooling Model

Call:
plm(formula = dep ~ indep, data = d, model = "pooling")

Balanced Panel: n=120, T=7, N=840

Residuals :
    Min.  1st Qu.   Median  3rd Qu.     Max.
-1.38000 -0.25500  0.00574  0.27900  1.41000

Coefficients :
                 Estimate Std. Error t-value Pr(>|t|)
(Intercept)     4.9648729  0.1521943 32.6219   <2e-16 ***
indepexperience 0.0156509  0.0013366 11.7092   <2e-16 ***
indepprojects   0.0036308  0.0027941  1.2994   0.1941
indepeduc       0.0962621  0.0047533 20.2517   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    204.01
Residual Sum of Squares: 131.14
R-Squared        :  0.3572
      Adj. R-Squared :  0.3555
F-statistic: 154.851 on 3 and 836 DF, p-value: < 2.22e-16
```

Analysis of OLS Pooled Panel Data

- Bad fit to the data
- Ignore the fact that it is a panel data
- Correlation of the error terms

Between Estimation Panel Data

- It calculates the average of the dependent and the independent variables over time and does the OLS regression of the former on the latter.

- Uses only cross-sectional information and discards time variation in the data.

- The between estimator is consistent only if the average of regressors over time are independent of the error term.

```
> between<-plm(dep~indep,data=d,model="between")
> summary(between)
Oneway (individual) effect Between Model

Call:
plm(formula = dep ~ indep, data = d, model = "between")

Balanced Panel: n=120, T=7, N=840

Residuals :
   Min. 1st Qu.  Median 3rd Qu.    Max.
-0.8780 -0.1770  0.0324  0.2200  0.7500

Coefficients :
                 Estimate Std. Error t-value  Pr(>|t|)
(Intercept)     4.8413875  0.4710134 10.2787 < 2.2e-16 ***
indepexperience 0.0124702  0.0030095  4.1436 6.526e-05 ***
indepprojects   0.0085089  0.0093326  0.9117    0.3638
indepeduc       0.0934853  0.0104833  8.9176 8.091e-15 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    21.844
Residual Sum of Squares: 12.617
R-Squared      :  0.42241
      Adj. R-Squared :  0.40833
F-statistic: 28.278 on 3 and 116 DF, p-value: 8.4878e-14
```

Analysis of OLS-Between Panel Data

- OLS-Between improves over OLS-Pooled as indicated by the R^2 value
- The Adjusted R^2 value also had an improvement

First Difference Estimation OLS

- Exploits the features of a panel data.
- Finds the association between the individual-specific changes in the repressors and the individual-specific changes in the dependent variable.
- It lags the individual-specific variables by one period and takes the difference between the two equations.
- Thus, individual heterogeneity is eliminated from the model.

OLS First Difference Estimation

Allows the data scientist to detect and study unobserved, hidden variables

Examples of possible unobserved, hidden variables:

- IQ of employee
- University the employee went to for studies
- Employees' parents' income
- Etc....

```
> fd<-plm(dep~indep,data=d,model="fd")
> summary(fd)
Oneway (individual) effect First-Difference Model

Call:
plm(formula = dep ~ indep, data = d, model = "fd")

Balanced Panel: n=120, T=7, N=840

Residuals :
    Min.   1st Qu.    Median   3rd Qu.     Max.
-1.05000 -0.07980 -0.00866  0.04950  1.36000

Coefficients :
               Estimate Std. Error t-value Pr(>|t|)
(intercept)   0.0957110  0.0068851  13.901  < 2e-16 ***
indepprojects 0.0027597  0.0012944   2.132  0.03335 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    24.659
Residual Sum of Squares: 24.504
R-Squared      :  0.0062906
      Adj. R-Squared :  0.0062731
F-statistic: 4.54525 on 1 and 718 DF, p-value: 0.033349
>
```

Analysis of OLS First Difference Estimation

- The variable “education” got dropped from the model.
- Education does not vary from one year to the next, thus difference between the education values for two consecutive years is zero.

Fixed Effects Panel Data

- Correlation between alfa$_i$ and X$_i$ is different from zero

- Treats the unobserved individual heterogeneity (αi)for each employee to be correlated with the explanatory variables.

- FE estimation involves a transformation to remove the unobserved effect αi prior to estimation.

Fixed Effects Panel Data

- FE Transformation
- $y_{it} = \beta_1 x_{it} + \alpha_i + u_{it}$ $t=1,2,\ldots,T$

- On averaging this equation over time,
- $y_i' = \beta_1 x_i' + \alpha_i + u_i'$
- Subtracting these two equations,
$(y_{it} - y_i') = \beta_1 (x_{it} - x_i') + (u_{it} - u_i')$ $t=1,2,..T$

- Differencing has led to elimination of α_i
- The LHS is called time-demeaned y.
- Similarly, time-demeaned x and u.

Fixed Effects - Within Estimation
Panel Data

- OLS can be applied on the time-demeaned equation. This is called FIXED EFFECTS / WITHIN ESTIMATION.

- This is because of the use of OLS on the time variation in x and y within each cross-sectional observation.

```
> fxd<-plm(dep~indep, data=d, model="within")
> summary(fxd)
Oneway (individual) effect Within Model

Call:
plm(formula = dep ~ indep, data = d, model = "within")

Balanced Panel: n=120, T=7, N=840

Residuals :
    Min.  1st Qu.   Median  3rd Qu.     Max.
-1.09000 -0.05740  0.00685  0.06610  0.84100

Coefficients :
                 Estimate Std. Error t-value Pr(>|t|)
indepexperience 0.1002007  0.0027065 37.0218  < 2e-16 ***
indepprojects   0.0027540  0.0014705  1.8729  0.06149 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    51.101
Residual Sum of Squares: 17.556
R-Squared       :  0.65644
      Adj. R-Squared :  0.5611
F-statistic: 685.943 on 2 and 718 DF, p-value: < 2.22e-16
>
```

Analysis of Fixed Effects - Within Estimation Panel Data

- The variable “education” is dropped because it is time invariant and gets cancelled.
- “experience” has a positive effect on the log salary.
- If the experience of an employee rises by one year, there is a 10% increase in wages.
- The R-square value 65.644% shows the amount of time variation in y it that is explained by time variation in Xit .

Random Effects Panel Data

- Correlation between $alfa_i$ and X_i is zero

- Assumes that the individual-specific effects are independent of the regressors.

- This individual-specific effect is included as the error term

```
> ran<-plm(dep~indep, data=d, model="random")
> summary(ran)
Oneway (individual) effect Random Effect Model
   (Swamy-Arora's transformation)

Call:
plm(formula = dep ~ indep, data = d, model = "random")

Balanced Panel: n=120, T=7, N=840

Effects:
                  var std.dev share
idiosyncratic 0.02445 0.15637 0.188
individual    0.10527 0.32446 0.812
theta:  0.8208

Residuals :
    Min.  1st Qu.   Median  3rd Qu.     Max.
-1.00000 -0.10700  0.00924  0.11400  1.04000

Coefficients :
                 Estimate Std. Error t-value Pr(>|t|)
(Intercept)     3.6239454  0.2093277 17.3123   <2e-16 ***
indepexperience 0.0606693  0.0025145 24.1280   <2e-16 ***
indepprojects   0.0015809  0.0018167  0.8702   0.3844
indepeduc       0.1327592  0.0129274 10.2696   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    56.012
Residual Sum of Squares: 32.031
R-Squared      :  0.42814
      Adj. R-Squared :  0.4261
F-statistic: 208.63 on 3 and 836 DF, p-value: < 2.22e-16
```

Linear Model Test for Random Effects VS OLS

- The LM is used to decide between a random effects regression and a simple OLS regression.
- Done using the plmtest function.
- The null hypothesis is that there is no significant difference across cross-sectional units.(i.e. no panel effect) implying that RE model is inappropriate.

```
> plmtest(pool)

        Lagrange Multiplier Test - (Honda)

data:  dep ~ indep
normal = 31.5945, p-value < 2.2e-16
alternative hypothesis: significant effects

>
```

Linear Model Test for Random Effects VS OLS

- The test statistic is 31.5945 and the p value is less than 0.05
- It is significant and the null hypothesis in favor of OLS is rejected.
- Thus, the Random Effects model is chosen against the OLS.

Linear Model Test for Fixed Effects VS OLS

- The LM test to choose between the fixed effects model and the OLS is done using the function pFtest on the fixed and pooled estimates.

- The null hypothesis is that there are no time-invariant effects and so OLS should be used.

```
> pFtest(fxd,pool)

        F test for individual effects

data:  dep ~ indep
F = 39.3652, df1 = 118, df2 = 718, p-value < 2.2e-16
alternative hypothesis: significant effects

>
```

Linear Model Test for Fixed Effects VS OLS

- The test statistic is 39.3652 and the p value is less than 0.05
- The null hypothesis is rejected thus implying that the Fixed effects model should be used instead of the OLS.

Hausman Test for Fixed Effects VS Random Effect

- The Hausman test is used to decide between the fixed effects model and the random effects model.

- This is done using the phtest (Panel Hausman Test) function.

```
> phtest(ran,fxd)

        Hausman Test

data:  dep ~ indep
chisq = 1557.3, df = 2, p-value < 2.2e-16
alternative hypothesis: one model is inconsistent
```

Hausman Test for Fixed Effects VS Random Effects

- The Chi Square test statistic is 1557.3 and the p value is less than 0.05

- As the null is rejected, the Fixed effects method is chosen to model the data instead of the random effects model.

Hands-on Exercise of Panel Data using Python

Download the Python script panel-data.py

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