these two are both individual effect

individual can mean widely, person, firm, etc. now, we consider it as person

$$y=X\beta+\epsilon$$
 if y = earning, x = 10, we, noramlly, say people with higher 10, earn more. But in this case, we can say, just because it is you, so you earn more, the independent variable is the person itself, even though it hard for use to estimate how the person itself affect his earning, we can know person does affect the earning, and we can use in other models

Fixed Effects vs Random Effects

notice, fixed effect is not "Fixed", so do random effect

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The Model

Consider the model: X1, Xk are change over time t, but all pha will not change over time to time

only i here, because each individual i have their own effect, and will be along the time t

$$y_{it} = \beta_0 + x_{1it}\beta_1 + x_{2it}\beta_2 \dots + x_{kit}\beta_k + \alpha_i + \epsilon_{it}$$
 (1)

Strict exogeneity assumption:

if this assumption doesn't hold, then you have to use IV to solve the problem.

$$E[\epsilon_{it}|x_i,\alpha_i]=0 (2)$$

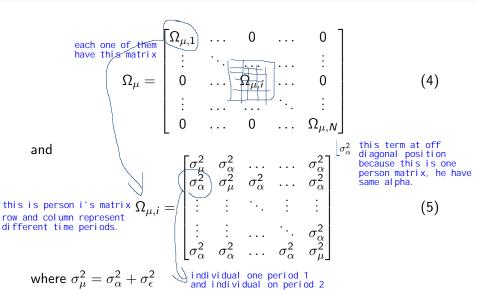
without alpha, if you regress y on x1 to xk, it works. But if there's alpha, you still regress y on x1 to xk, with assumption below,

 $E[\epsilon_{it}|x_i,\alpha_i]=0$ $E[\alpha_i|x_i]=0$ alpha and epsilon are both not related to X, then OLS works you consider the error term as a combination of α_i)+ ϵ_{it}

- In the random effects model, we have to make the "unrelated effects" assumption: alpha should not be related with X, you should know, most of the time this assumption doesn't hold $E[\alpha_i|x_i] = 0$ so, you need to argue it. (3) with this assumption, we are ok to omit alpha, as it doesn't affect x
 - Under this assumption, we do know that the Pooled OLS is unbiased and consistent. We just treat the whole $\alpha_i + \epsilon_{it} = \mu_{it}$ as the error term and run an OLS regression.
 - However, since we know about the error μ_{it} , we can run a GLS estimation instead:

random effect is unbiased and consistent

Random Effects



Random Effects

the estimator we get, you can call it FGLS estimator or random effect estimator

- And we can estimate the Ω_{μ} by $\hat{\Omega}_{\mu}$
- First, we run the Pooled OLS and obtain the residual
- Then we use the residual $\hat{\sigma}_{\mu}$ to calculate the required elements

$$\hat{\sigma}_{\mu}^{2} = \frac{1}{NT} \sum_{t=1}^{T} \sum_{i=1}^{N} \hat{\mu}_{it}^{2}$$
 (6)

$$\frac{10}{\frac{1}{1}} \frac{t}{\frac{\hat{\beta}_{it}}{\hat{\beta}_{it}}} \frac{\hat{\beta}_{it}^{2}}{\hat{\beta}_{it}^{2}} \frac{\hat{\beta}_{it}^{2$$

$$\hat{\sigma}_{\alpha}^2 = \hat{\sigma}_{\mu}^2 - \hat{\sigma}_{\epsilon}^2 \tag{8}$$

BUT both of them need this: $E[\epsilon_{it}|x_i,\alpha_i]=0$

Fixed Effects

we can use fixed effect and IV together if X is endogenous

- In the fixed effects model we do not need the unrelated effect assumption.
- However, we need to ensure that there are no time-invariant regressors in x.
- There are three ways to compute the fixed effects estimator

unbilased and consistent

- all of them are Demeaned regression this means take away mean
 - Individual Dummies usually use this
 - First Differencing

Demeaned regression always gives you the same result (beta) as individual dummies

normally, when people say individual effect, they mean fixed effect, except they mention it is random effect

random effect: solve error term and run GLS, fiex effect: try to put the omit variable alpha back to the regression

without this assumption, $E[\alpha_i|x_i]=0$, in fixed effects, we cannot omit alpha

fixed effect is unbiased and consistent, but not blue.

For the demeaning regression, we can just take the time-average of the model

can we do both time fixed effects and dummy variable together? of course yes! someone may say you will lose degree of freedom. It is really a tricky argument

this is for each individual over time, not a sum of all indi vi dual s

$$\bar{y}_i = \frac{1}{T} \sum_t y_{it}$$

$$\bar{x}_{1i} = \frac{1}{T} \sum_t x_{1it}$$

$$\bar{x}_{2i} = \frac{1}{T} \sum_t x_{2it}$$

$$\bar{y}_i = \frac{1}{T} \sum_t x_{2it}$$

$$\bar{x}_{2i} = \frac{1}{T} \sum_t x_{2it}$$

$$\bar{x}_{3i} = \frac{1}{T} \sum_t x_{3it}$$

$$\bar{\mathbf{x}}_{1i} = \frac{1}{T} \sum_{t} \mathbf{x}_{1it}$$

$$\bar{x}_{ki} = \frac{1}{T} \sum_{t} x_{kit}$$

$$\bar{y}_{it} = \frac{1}{T} \sum_{t} x_{kit}$$

 $\bar{\alpha}_i = \frac{1}{T} \sum \alpha_i = \alpha_i$

alpha bar = alphaas for each person alphas are same ie: (5+5+5)/3 = 5

(14)

(13)



individual - time effect news

podividual and time fixed effect topedo

Therefore,

recall,
$$y_{it} = \beta_0 + x_{1it}\beta_1 + x_{2it}\beta_2... + x_{kit}\beta_k + \alpha_i + \epsilon_{it}$$

$$y_{it} - \bar{y}_i$$

$$= (x_{1it} - \bar{x}_{1i})\beta_1 + (x_{2it} - \bar{x}_{2i})\beta_2... + (x_{kit} - \bar{x}_{ki})\beta_k$$

$$+ (\alpha_i - \alpha_i) + \epsilon_{it} - \bar{\epsilon}_i$$
now you are regressing $y_{it} - \bar{y}_i$ on $(x_{1it} - \bar{x}_{1i})$, $(x_{2it} - \bar{x}_{2i})$... rath

now you are regressing $y_{it}-\bar{y}_i$ on $(x_{1it}-\bar{x}_{1i})$, $(x_{2it}-\bar{x}_{2i})$...rather y on x this is a totally different regression, but the math tell us the betas will not change. True beta doesn't change, but the beta hat you get can be a little bit different.

$$y_{it} - \bar{y}_{i}$$

$$= (x_{1it} - \bar{x}_{1i})\beta_{1} + (x_{2it} - \bar{x}_{2i})\beta_{2}... + (x_{kit} - \bar{x}_{ki})\beta_{k}$$

$$+ \epsilon_{it} - \bar{\epsilon}_{i}$$

Notice: through this method, different with what we recalled, we do not have individual effect(alpha) anymore.

Or we can have dummy variables for each individuals:

we know how many individual in data, then we add n-1 alphas

Which one is better?

for dummy, we can actually estimate the exact each person's individual effect(alpha), but demeaning cannot. so if you care more in alpha, use dummy. But

if you have 1 million obs, then you have to estimate (1 million - 1) more variables. demeaning will run faster(but lose 1 degree of freedom for each individual), dummy give you too much computational burden. obs>100,000, your regression will run slow. so demeaning is better than dummy variable

by controlling all other X and alpha, for X1, if ob1 and ob2 have different X and Y, then we can attribute this difference to individual effect.

Finally, we have the first differencing:

$$y_{it} = \beta_0 + x_{1it}\beta_1 + x_{2it}\beta_2 \dots + x_{kit}\beta_k + \alpha_i + \epsilon_{it}$$
 (15)

$$y_{it+1} = \beta_0 + x_{1it+1}\beta_1 + x_{2it+1}\beta_2 \dots + x_{kit+1}\beta_k + \alpha_i + \epsilon_{it+1}$$
 (16) this eq estimate next period.

The difference between two equations gives:

$$y_{it+1} - y_{it}$$
= $(x_{1it+1} - x_{1it})\beta_1 + (x_{2it+1} - x_{2it})\beta_2 ... + (x_{kit+1} - x_{kit})\beta_k$
+ $\epsilon_{it+1} - \epsilon_{it}$

by this method, we lose 1 time period data(ob) for each individual first differencing is same as demeaning only when we have 2 period obs. so if you only have 2 period, use first differencing! but for this method, if you use (Yit+2 - Yit) or (Yit+3 - Yit) the model gives you same betas (slightly different). we don't know which one is better.