

# Econ 272/Mgtecon 607 - Section 2

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1. Announcements
2. Discussion Questions
3. Clustered Experiments
4. Clustering in Sampling and in Assignment
5. Practice Problems

1. Announcements

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- Remember to email me about whether you wish to take the final exam, and if you require any special accommodations for it
  - Unless you are an Econ PhD, in which case you have no choice :)
  - If you are a predoc and wish to waive the class next year, you must take the exam as well

## Hints for Problem Set 2 (Due April 13, 11pm)

- Within-group correlations of a single variable try to answer the question: does *my* value going up mean that *your* value is more likely to go up/down?
  - $\text{Corr}(Y_i, Y_j)$  for  $i \neq j$  can be calculated by constructing pairs (combinatorially) of observations from the data

- Recall the definition/equation for correlation - how can it be simplified in this context?

$$\begin{aligned} \text{Corr}(Y_i, Y_j) &= \frac{\text{Cov}(Y_i, Y_j)}{\sqrt{\text{Var}(Y_i)\text{Var}(Y_j)}} = \frac{\text{Cov}(\tilde{Y}_i, \tilde{Y}_j)}{\text{Var}(\tilde{Y}_i)} = E[\tilde{Y}_i \tilde{Y}_j] - E[\tilde{Y}_i]E[\tilde{Y}_j] \\ \tilde{Y}_i &= \frac{Y_i - \bar{Y}}{\sigma_Y} \end{aligned}$$

*Handwritten notes:*

- A small table with  $\tilde{Y}$  in the first column and  $P_{\tilde{Y}}$  in the second column, with vertical dots below each.
- The expression  $\frac{1}{\binom{N}{2}} \sum_{i \neq j} \tilde{Y}_i \tilde{Y}_j$  with a bracket under the sum.
- An arrow pointing from the  $E[\tilde{Y}_i]E[\tilde{Y}_j]$  term to a circled  $\tilde{Y}_i$  in the sum.

- Simplified equations for LZ/EHW variance estimators on slides (Lecture 4, Slide 4) are missing a factor of  $1/N$

## A note on terminology

- In the course, we will often use the term “population” to refer to the experimental sample since we are mainly thinking about design-based inference
- We will therefore refer to the broader population from which the experimental sample is drawn as the “super-population”
- We may occasionally refer to our experimental sample as the “sample”, for example when we want to distinguish between sample and population ATEs
- It is confusing, I will try to be as explicit as possible

## From last time: nontrivial sharp nulls

Test statistic for sharp null:  $Y_i(1) = a \cdot Y_i(0) + b$

$$\begin{aligned} T &= \bar{\tilde{Y}}_i(1) - \bar{\tilde{Y}}_i(0) \\ &= \bar{Y}_i(1) - a \bar{Y}_i(0) - b \end{aligned}$$

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## Discussion Questions - Clustered Randomized Experiments

- 1 What is the difference between clustered sampling and clustered assignment?
- 2 What is the thought experiment underlying clustered standard errors? When should you (not) use them?
- 3 What is the difference between a clustered randomized experiment and a stratified randomized experiment?
- 4 Should we prefer clustered or non-clustered randomized experiments? Why are we studying both?

## Discussion Questions - Clustering in Sampling and in Assignment

- 1 What are the traditional frameworks for thinking about clustering standard errors? What are their drawbacks?
- 2 What do we mean by design-based clustering?
- 3 Does the data tell us whether we need to cluster our standard errors or not?
- 4 What is the new variance that takes into account clustering in sampling and in assignment? How does it compare to the Neyman/robust variance and the cluster-robust variance (Liang-Zeger)?
- 5 How can we estimate this variance?

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## Why cluster?

Spillovers, network effects  $\rightarrow$  SUTVA violations


My outcome depends on your treatment

Idea: If spillovers occur on specific clusters  
treating clusters as units.

# Clustered Sampling vs. Assignment

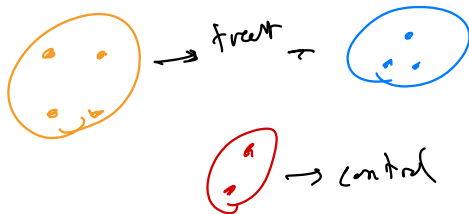
## ■ Clustered Sampling:



 → Unsampled  
 $C_1, C_2, C_3$   
Pool 2

## ■ Clustered Assignment:

helps  
spillovers



- $G$ : Clusters
- $G_i \in \{1, \dots, G\}$ : cluster assignment for unit  $i$
- $N_g$ : # units in cluster  $g$  ( $N = \sum_g N_g$ )

## ■ Estimands:

$$\tau_{\text{ITT}} = \frac{1}{n} \sum_i Y_i(1) - Y_i(0)$$

overall 2x2 ATB

= if  $N_g = n$  for  
if ITT cluster

$$\tau_{\text{cluster}} = \frac{1}{G} \sum_g \left( \frac{1}{n_g} \sum_i Y_i(1) - Y_i(0) \right)$$

overall cluster-level ATB

## ■ Estimators:

$$\hat{\tau}_{\text{ITT}} = \bar{Y}_1 - \bar{Y}_0$$

had to estimate  
prevalence

$$\hat{\tau}_{\text{cluster}} = \frac{1}{G_1} \sum_g \left( \frac{1}{n_g} \sum_i w_i Y_i \right) - \frac{1}{G_0} \sum_g \left( \frac{1}{n_g} \sum_i (1-w_i) Y_0 \right)$$

Both estimators are unbiased

Variance:  $\hat{\tau}_{cluster}$



$$\rightarrow V_{regression} = \frac{S_0^2}{N_0} + \frac{S_1^2}{N_1} - \frac{S_{01}^2}{N}$$

■ True Variance:

$$Var(\hat{\tau}_{cluster}) = \frac{S_0^2}{G_0} + \frac{S_1^2}{G_1} - \frac{S_{01}^2}{G}$$

■ Estimator:

$$\hat{Var}(\hat{\tau}_{cluster}) = \frac{\hat{S}_0^2}{G_0} + \frac{\hat{S}_1^2}{G_1}$$

$$S_u^2 = \frac{1}{G-1} \sum_g (\bar{Y}_g(u) - \bar{Y}_{g(u)})^2$$



Variance:  $\hat{\tau}_{pop}$

Challenge: treatment assignment not indep.

■ True Variance: Asymptotics: sequence of pops.  $k=1, 2, \dots$

In pop.  $k$ , sample all units, assign each  $g$  to treatment v.e.  $\theta$

For  $N_g$  pops, let  $G_k, N_k \rightarrow \infty$ :

$$\sqrt{N_k} (\hat{\tau}_{gk} - \tau_{gk}) \xrightarrow{d} N(0, \underbrace{V_k}_{\substack{\text{eqn on} \\ \text{slide} \\ 24}})$$

■ Estimator: Conservative estimate var:  $y_i = \alpha + \beta w_i + \epsilon_i$

$$\underbrace{\hat{V}_{\text{cluster}}}_{\hat{V}_{L2}} = \left( \frac{1}{n} \sum_i w_i^2 \right)^{-1} \left( \frac{1}{n} \sum_i \sum_j (y_i - \bar{y}_j)^2 \right) \left( \frac{1}{n} \sum_i w_i^2 \right)^{-1}$$
$$\bar{w} = w_i - \frac{1}{n} \sum_{j \neq i} w_j$$
$$(\geq V_{\text{EHW}})$$

Inference based on rand. dist. induced by  
clustered assignments, rather than indiv.

Typically rely asymptotically.

But, Fisher exact & STM work, but none of  
analyses are clusters

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## 2 "Flavors" of Error / Variability

1 Sampling - how sample constructed

2 Assignment - how treatment assigned

Don't needed for inference in causal settings  
→ Abadie et. al. (2003) (general framework)

## (Even More) Notation

Sequences of populations indexed by  $k = 1, 2, 3, \dots$

■  $g_k$ : # clusters in  $k$

■  $n_{g,k}$ : # units in cluster  $g$  in popn  $k$

■  $q_k \in (0, 1]$ : cluster sampling probability in popn  $k$   $\left\{ \begin{array}{l} q_k = 1 : \text{random sampling} \\ q_k < 1 : \text{clustered sampling} \end{array} \right.$

■  $p_k$ : prob. a unit is sampled from cluster

■  $A_{k,g}$ : prob. unit in cluster  $g$  in popn  $k$  is included:  $A_{k,g} \sim (\mu_k, \sigma_k^2)$

not all clusters need be sampled

not all units need same treatment within cluster

} Nest C.S.  
+  
C.A.

# Clustering Regimes

$q_k, \sigma_k^2, \mu_k$   
 $\downarrow$  Sampling  
 $\underbrace{\sigma_k^2, \mu_k}_{\text{assignment}}$

		Assignment, $A_{k,g}$		
		Random	Partially Clustered	Clustered
Sampling $q_k$	Random	$q_k = 1, \sigma_k^2 \geq 0$	$q_k \geq 1,$	$q_k = 1, \sigma_k^2 \geq \mu_k(1+\mu_k)$
	Clustered	$q_k < 1, \sigma_k^2 \geq 0$	$0 < \sigma_k^2 < \mu_k(1-\mu_k)$ $q_k < 1,$	$\downarrow$ $q_k < 1,$

- Random sampling of clusters from a large population of clusters  $\rightarrow p_k$  small
- Random sampling from a large population  $\rightarrow p_k=1, p_k$  small
  - Completely random assignment  $A_{k,g} = A_k$  ( $\sigma_k^2 = 0$ )
  - Clustered random assignment  $A_{k,g} \in \{0, 1\}$
- What can we test?

can test  $p_k = 1$  vs.  $< 1$

can test  $\sigma_k^2 = 0$  vs.  $\geq 0$

## Causal Cluster Variance (CCV) - Big Idea

Asymptotic DM converges:  $\sqrt{N_k} (\hat{\tau}_k - \tau_k) \xrightarrow{d} N(0, V_k^{CCV})$

$$V_k^{CCV} = V_k^{CCV}(q_k, \sigma_k^2, q_k, \mu_k)$$

Special cases:

$$V_k^{BEH} \approx V_k^{CCV}(q_k=1, \sigma_k^2=0)$$

$$V_k^{LZ} - V_k^{CCV} \geq 0 \rightarrow LZ \text{ conservative}$$

$$V_k \hat{\tau}^{DM} \text{ to est. } \tau_{PT}$$



$$R_k \quad \hat{\Sigma}^{\text{Dim}} \rightarrow \Sigma_{\text{reg}}$$

		Assignment, $A_{k,g}$		
		Random	Partially Clustered	Clustered
Sampling $q_k$	Random	L2+W	CCV	L2
	Clustered	CCV	CCV	CCV

$$\downarrow$$

$$\approx L2 \text{ or } q_k \text{ small}$$

$$\text{If } q_k \text{ small, } E(L+W) \approx L2 \approx CCV$$

$$\sigma_z^2 \rightarrow 0, \hat{V}^{ccv} \rightarrow \hat{V}^{\text{EHV}} \quad \sigma_z^2 \rightarrow \mu_k(v\mu_k), \hat{V}^{ccv} \rightarrow \hat{V}^{L2}$$

$$\textcircled{1} \text{ Analytic: } \hat{V}_k^{ccv} = \underbrace{\hat{q}_k}_{\substack{\text{knowledge} \\ \text{on the \# of classes in } \mathcal{Z}_{\text{em}}}} \cdot \hat{V}_k^{ccv}(1) + \overset{L_k \rightarrow 0}{(1 - \hat{q}_k)} \hat{V}_k^{L2}$$

$$\textcircled{2} \text{ Bootstrap: } \text{TSCB}$$

# Variance Estimation by Regime

		Assignment, $A_{k,g}$		
		Random	Partially Clustered	Clustered
Sampling $q_k$	Random	$\hat{V}^{ELW}$	$\hat{V}^{CCV} \rightarrow \hat{V}^{LZ} \rightarrow \hat{V}^{CCV}(1)$	$\hat{V}^{LZ}$
	Clustered	$\hat{V}^{CCV}$	$\hat{V}^{CCV}$	$\hat{V}^{CCV}$

Note: the choice of estimator really matters here!! Standard errors can vary widely. TSCEB

LZ: if wanted unbiased class on trying to estimate

ELW: if drawing clusters local to some

CCV: if imbalanced, or if you use clustered sampling

not available

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Suppose California is setting up a new job training program. To understand the impact a pilot program is set up where 10% of eligible individuals in 20 counties in California are randomly assigned to the new program. The outcome of interest is labor market status six months from randomization. Let  $Y_i$  denote the outcome, let  $W_i \in \{0, 1\}$  denote the treatment, and let  $S_i$  denote the county.

- (a) Describe how you could test the null hypothesis that there is no effect of the program whatsoever. Discuss all the choices you make in this implementation. ↗ exact ↖
- (b) Describe how you would estimate the average effect of the program. ↗  $\hat{\tau}^{DiM}$  ↖
- (c) Describe how you would estimate the variance of this estimator, with and without clustering. ↗  $\hat{V}^{LZ}$  ↖
- (d) Should you cluster here? What are the arguments for or against?

Suppose we conduct a randomized experiment on a random sample of the US population. We assign the treatment randomly at the state level. The dataset observed by the econometrician includes individual-level outcomes, location (state) for each individual, and a treatment indicator that corresponds to the state.

- (a) How would you estimate the average effect of the treatment?
- (b) How would you estimate the variance of the estimator?

Suppose we conduct a randomized experiment on a random sample of the US population. We assign the treatment randomly at the state level. The dataset observed by the econometrician includes individual-level outcomes, location (state) for each individual, and a binary treatment indicator that is the same within each state.

(a) Suppose you estimated the average treatment effect as the difference in means by treatment status, give an expression for the variance of the estimator, and how you could estimate the unknown components of that variance?

(b) Suppose you used the Neyman variance estimator that ignored the state-level randomization and that was based on individual level randomization. Would you expect that to over or under estimate the true variance?