

# Randomized Control Trials and Policy Evaluation

Matteo Bobba

[matteo.bobba@tse-fr.eu](mailto:matteo.bobba@tse-fr.eu)

Office: T.353

Toulouse School of Economics (TSE)

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# Part 2: Econometrics of RCTs

## ① The basic framework

- ⇒ Potential outcomes, SUTVA (IR, Ch 1) and covariates
- ⇒ Assignment mechanisms and randomized experiments (IR, Ch 3,4)

## ② Statistical analysis of experiments

- ⇒ Completely randomized experiments (IR Ch 5,7)
- ⇒ Stratified randomized experiments (IR Ch 9)
- ⇒ Pairwise randomized experiments (IR Ch 10)
- ⇒ Clustered randomized experiments (AI Section 8)
- ⇒ Adaptive randomized experiments

## Potential outcomes and SUTVA

# Causal Inference as a Missing Data Problem

- Population of units, indexed by  $i = 1, \dots, N$
- Treatment indicator  $W_i$  taking values 0 and 1
- For  $i \in \{1, \dots, N\}$   $\exists$  one realized outcome and one missing potential outcome

$$Y_i^{\text{obs}} = Y_i(W_i) = \begin{cases} Y_i(0) & \text{if } W_i = 0 \\ Y_i(1) & \text{if } W_i = 1 \end{cases}$$

$$Y_i^{\text{miss}} = Y_i(1 - W_i) = \begin{cases} Y_i(1) & \text{if } W_i = 0 \\ Y_i(0) & \text{if } W_i = 1 \end{cases}$$

⇒ Unit-level causal effect  $Y_i(1) - Y_i(0)$  is unobserved

# Causal Inference as a Missing Data Problem

- Potential outcomes in terms of the observed and missing outcomes

$$Y_i(0) = \begin{cases} Y_i^{\text{miss}} & \text{if } W_i = 1 \\ Y_i^{\text{obs}} & \text{if } W_i = 0 \end{cases}$$

$$Y_i(1) = \begin{cases} Y_i^{\text{miss}} & \text{if } W_i = 0 \\ Y_i^{\text{obs}} & \text{if } W_i = 1 \end{cases}$$

- ⇒ If we **impute the missing outcomes** we know all the potential outcomes
- ⇒ and thus the value of any causal estimand in the population of  $N$  units

# Potential Vs. Observed Outcomes: An Example

Unit	Potential Outcomes		$Y_i(1) - Y_i(0)$	Causal Effect		
	$Y_i(0)$	$Y_i(1)$		Unit	Treatment	Observed Outcome
			$i$	$W_i$	$Y_i^{\text{obs}}$	
Patient #1	1	7	6	Patient #1	1	7
Patient #2	6	5	-1	Patient #2	0	6
Patient #3	1	5	4	Patient #3	1	5
Patient #4	8	7	-1	Patient #4	0	8
Average	4	6	2			

- $E(Y_i(1) - Y_i(0)) > 0$ , while  $E(Y^{\text{obs}} \mid W_i = 1) - E(Y^{\text{obs}} \mid W_i = 0) < 0$
- ⇒ Selection bias:  $W_i \not\perp (Y_i(1), Y_i(0))$

# The Stable Unit Treatment Value Assumption (SUTVA)

- We will generally need to predict the missing potential outcomes
- To do so, we need the following assumption:

*The potential outcomes for any unit do not vary with the treatments assigned to other units, and, for each unit, there are no different forms or versions of each treatment level, which lead to different potential outcomes.*

# SUTVA: No interference

- $W_{-i} = (W_j)_{j \neq i}$ : treatment status of all other obs. in the sample except  $i$
- The no interference part of SUTVA requires that

$$W_{-i} \perp (Y_i(1), Y_i(0))$$

⇒ For all  $y_1, y_0$  and  $w$ :

$$\begin{aligned}\Pr(Y_i(1) \leq y_1, Y_i(0) \leq y_0, W_{-i} = w) &= \\ \Pr(Y_i(1) \leq y_1, Y_i(0) \leq y_0) \Pr(W_{-i} = w)\end{aligned}$$

# SUTVA: Scale invariance

- Imagine two versions of treatment:  $W = \{0, 1, 2\}$
- The scale invariance part of SUTVA requires that

$$\Rightarrow Y_i(1) = Y_i(2)$$

$$\Rightarrow \begin{cases} \{Y_i(1) & \forall i = 1, \dots, M\} \\ \{Y_i(2) & \forall i = M + 1, \dots, N, M < N\} \end{cases}$$

$\Rightarrow W$  randomized across three values (stochastic treatment)

# Example of Possible SUTVA Violations

## ① No interference

- ⇒ Fertilizer in one plot may affect yields in contiguous plots
- ⇒ Immunization efficacy may depend on the number of people immunized
- ⇒ Prob(job) after training may be affected by the number of people trained

## ② Scale invariance

- ⇒ Endogenous compliance to treatment assignment
- ⇒ Unobserved differences in the method of administering the treatment

# The Role of Covariates in RCTs

- **Background attributes** can help predicting the missing potential outcomes
  - ⇒ Test assumptions about the assignment mechanism
  - ⇒ Increase estimates' precision by explaining some of the variation in outcomes
  - ⇒ Causal effect of the treatment on sub-groups in the population of interest
- Notice that  $W_i \perp (Y_i(1), Y_i(0)) \Rightarrow W_i \perp (Y_i(1), Y_i(0) | X_i)$ 
  - ⇒ But  $W_i \perp (Y_i(1), Y_i(0) | X_i) \not\Rightarrow W_i \perp (Y_i(1), Y_i(0))$

# Covariance Balance: Sanity Checks for the Randomization

- The distribution of covariates should be the same under treat and control

$$E(X_i | W_i = 1) \approx E(X_i | W_i = 0), \forall X_i \in \mathbf{X}_i$$

- A useful implication is that  $W_i$  is not predictable by  $\mathbf{X}_i$

$$E(W_i | \mathbf{X}_i) = E(W_i)$$

⇒ Both conditions are **testable**

# Improving Precision

- Lets assume that the conditional expectation function (CEF) is linear:

$$E(Y_i | W_i, \mathbf{X}_i) = \alpha + \beta W_i + \boldsymbol{\gamma}' \mathbf{X}_i, E(\mathbf{X}_i) = 0$$

- OLS estimation recovers ATE even if the regression is incorrectly specified

$$\begin{aligned}\beta &= E(Y_i(1) - Y_i(0)) \\ &= E(Y_i | W_i = 1) - E(Y_i | W_i = 0)\end{aligned}$$

⇒  $W_i \perp \mathbf{X}_i$ , even though in finite sample this correlation may differ from zero

# Improving Precision

- The Variance of the ATE is

$$V(\beta) = \frac{\sigma_{Y|W,X}^2}{\sum_{i=1}^N (W_i - \bar{W})^2}$$

- $\sigma_{Y|W,X}^2 < \sigma_{Y|W}^2$ : covariates increase precision of the ATE estimator
  - ⇒ Improvement in precision is not guaranteed in the linear model
- At the cost of loosing (exact) unbiasedness in finite samples

# Heterogenous Treatment Effects

- Let's consider the interactive linear regression model

$$E(Y_i | W_i, \mathbf{X}_i) = \alpha + \beta W_i + \boldsymbol{\delta}' \mathbf{X}_i W_i + \boldsymbol{\gamma}' \mathbf{X}_i, E(\mathbf{X}_i) = 0$$

- The Conditional Average Treatment Effect (CATE) is

$$\begin{aligned}\boldsymbol{\delta}(\mathbf{X}) &= E(Y_i(1) | \mathbf{X}_i) - E(Y_i(0) | \mathbf{X}_i) \\ &= E(Y_i | W_i = 1, \mathbf{X}_i) - E(Y_i | W_i = 0, \mathbf{X}_i)\end{aligned}$$

- ⇒ The vector  $\boldsymbol{\delta}(\mathbf{X})$  describes the deviation of CATE from the ATE,  $\beta$
- ⇒ The interactive approach always delivers improvements in precision

# Assignment Mechanisms

# Assignment Mechanism

- $N$  units, set  $\mathbb{W} = \{0, 1\}^N$  of  $N$ -vectors with all elements equal to 0 or 1
- ⇒ The assignment mechanism is a function  $P(\mathbf{W}|\mathbf{Y}(0), \mathbf{Y}(1)) \in [0, 1]$  such that

$$\sum_{W \in \{0,1\}^N} P(\mathbf{W}|\mathbf{X}, \mathbf{Y}(0), \mathbf{Y}(1)) = 1$$

- $P(\cdot)$  is the probability that a value for the joint assignment will occur
  - ⇒ It is not the probability of a particular unit receiving the treatment
  - ⇒ Some assignment vectors  $\mathbf{W}$  may have zero probability

# Assignment Probability and Propensity Score

- The unit-level assignment probability is:

$$p_i(\mathbf{X}, \mathbf{Y}(0), \mathbf{Y}(1)) = \sum_{\mathbf{W}: W_i=1} P(\mathbf{W} | \mathbf{X}, \mathbf{Y}(0), \mathbf{Y}(1))$$

- The propensity score at  $x$  is the average  $p_i(\cdot)$  for units with  $X_i = x$

$$e(x) = \frac{1}{N(x)} \sum_{i: X_i=x} p_i(\mathbf{X}, \mathbf{Y}(0), \mathbf{Y}(1))$$

$$\Rightarrow N(x) = \sum_{i: X_i=x} \mathbf{1}_{X_i=x}$$

$\Rightarrow$  For values  $x$  with  $N(x) = 0$ , the propensity score is defined to be zero

$\Rightarrow p_i(\mathbf{Y}(0), \mathbf{Y}(1)) = e$  in randomized experiments with no covariates

# Example of Assignment Mechanism 1

- Two units, and so ( $2^2$ ) possible values for  $\mathbf{W}$

$$\mathbb{W} \in \left\{ \begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 0 \\ 1 \end{pmatrix}, \begin{pmatrix} 1 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 \\ 1 \end{pmatrix} \right\}$$

- ⇒ The assignment mechanism is equal to  $P(\mathbf{W}|\mathbf{Y}(0), \mathbf{Y}(1)) = \frac{1}{4}$
- ⇒ Unit assignment probability  $p_i = p = \frac{1}{2}$  for  $i = 1, 2$
- ⇒ No covariates, and so propensity score  $e = p = \frac{1}{2}$

## Example of Assignment Mechanism 2

- Two units where only assignments with one treated and one control unit

⇒ The assignment mechanism is

$$P(\mathbf{W}|\mathbf{Y}(0), \mathbf{Y}(1)) = \begin{cases} 1/2 & \text{if } \mathbf{W} \in \left\{ \begin{pmatrix} 0 \\ 1 \end{pmatrix}, \begin{pmatrix} 1 \\ 0 \end{pmatrix} \right\} \\ 0 & \text{if } \mathbf{W} \in \left\{ \begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 \\ 1 \end{pmatrix} \right\} \end{cases}$$

⇒ As before,  $e = p = \frac{1}{2}$

# Restrictions on the Assignment Mechanism

## ① Individualistic

$$p_i(\mathbf{X}, \mathbf{Y}(0), \mathbf{Y}(1)) = q(X_i, Y_i(0), Y_i(1)), \quad q(\cdot) \in [0, 1]$$

## ② Probabilistic

$$0 < p_i(\mathbf{X}, \mathbf{Y}(0), \mathbf{Y}(1)) < 1$$

## ③ Unconfounded

$$P(\mathbf{W}|\mathbf{X}, \mathbf{Y}(0), \mathbf{Y}(1)) = P(\mathbf{W}|\mathbf{X}, \mathbf{Y}'(0), \mathbf{Y}'(1)) = P(\mathbf{W}|\mathbf{X})$$

# Randomized Experiments

- A regular assignment mechanism satisfies the three restrictions
- Regular assignment mechanisms with known  $P(\cdot)$  are randomized experiments
- Individualistic + unconfounded  $\rightarrow$  the assignment mechanism is

$$P(\mathbf{X}, \mathbf{Y}(0), \mathbf{Y}(1)) = c \cdot \prod_{i=1}^N q(X_i)^{W_i} (1 - q(X_i))^{1-W_i}$$

$\Rightarrow$  The constant  $c$  ensures that the probabilities add to unity

$\Rightarrow e(x) = p_i(x) = q(x)$

# An Example: Bernoulli Trials (Coin Tossing)

- $p = e = 0.5, \mathbb{W}^+ = \{0, 1\}^N$

$$P(\mathbf{W}|\mathbf{X}, \mathbf{Y}(0), \mathbf{Y}(1)) = 0.5^N$$

- More generally, with probability of assignment to treatment  $\neq 0.5$

$$P(\mathbf{W}|\mathbf{X}, \mathbf{Y}(0), \mathbf{Y}(1)) = q^{N_t} (1 - q)^{N_c}$$

⇒ No way to ensure “enough” treated and control units under each assignment

# Taxonomy of Randomized Experiments

# Basic Designs

- Let the set of possible assignments  $\mathbb{W}$  with positive prob. be denoted by  $\mathbb{W}^+$
- Randomization designs can be characterized by [restrictions on  \$\mathbb{W}^+\$](#) 
  - ⇒ Completely randomized experiments
  - ⇒ Stratified randomized experiments
  - ⇒ Pairwise randomized experiments

# Completely Randomized Experiments

- Draw  $N_t$  units at random, such that  $1 \leq N_t \leq N - 1$
- $q = \frac{N_t}{N}$ , and the number of possible assignments is  $\binom{N}{N_t}$
- The set of possible assignment vectors is

$$\mathbb{W}^+ = \left\{ \mathbf{W} \in \mathbb{W} \mid \sum_{i=1}^N W_i = N_t \right\}$$

⇒ Possible issue with covariate unbalancedness after treatment assignment

# Stratified Randomized Experiments

- The population of units is first partitioned into **blocks or strata**  $B_i = B(\mathbf{X}_i)$
- Within each block, we conduct a completely randomized experiment
- The set of possible assignment vectors is

$$\mathbb{W}^+ = \left\{ \mathbf{W} \in \mathbb{W} \mid \sum_{i:B_i=j}^N W_i = N_t(j) \right\}$$

⇒ More precise inference as units of same type are in different treat arms

# Paired Randomized Experiments

- As many units as treatments within each block
- $N(j) = 2$  and  $N_t(j) = 1$  for  $j = 1, \dots, N/2$ , so that

$$\mathbb{W}^+ = \left\{ \mathbf{W} \in \mathbb{W} \mid \sum_{i:B_i=j}^N W_i = 1 \right\}.$$

⇒ Useful design when  $N$  is small and/or  $J$  is large

# Number of Possible Values for the Assignment Vector

Type of Experiment and Design	Number of Possible Assignments Cardinality of $\mathbb{W}^+$	Number of Units ( $N$ ) in Sample			
		4	8	16	32
Bernoulli trial	$2^N$	16	256	65,536	$4.2 \times 10^9$
Completely randomized experiment	$\binom{N}{N/2}$	6	70	12,870	$0.6 \times 10^9$
Stratified randomized experiment	$\binom{N/2}{N/4}^2$	4	36	4,900	$0.2 \times 10^9$
Paired randomized experiment	$2^{N/2}$	4	16	256	65,536

# More Sophisticated Designs

- Popular experimental designs in the social sciences
  - ⇒ Clustered randomized experiments
  - ⇒ Randomized saturation experiments
  - ⇒ Adaptive randomized experiments

# Clustered Randomized Experiments

- Clusters are defined by partitioning the covariate space  $G_{ig} = G(\mathbf{X}_i)$
- $\bar{W}_g = \sum_{i:G_{ig}=1} \frac{W_i}{N_g} \in \{0, 1\}$  is the average value of  $W_i$  for units in cluster  $g$
- The assignment mechanisms concerns groups of units (clusters)

$$\mathbb{W}^+ = \left\{ \mathbf{W} \in \mathbb{W} \mid \sum_{g=1}^G \bar{W}_g = G_t \right\}$$

⇒ Relax SUTVA within clusters, but maintain it across clusters

# Randomized Saturation Experiments

- A variant of clustered randomization where
  - ⇒ Assign each cluster to a treatment saturation,  $S_g = \sum_{i \in g} W_{ig} \in [0, 1]$
  - ⇒ Assign each individual to a treatment status  $W_{ig} = \{0, 1\}$  according to  $S_g$
- This design is aimed at measuring local spillovers/equilibrium effects
- Optimal combination of clustered and stratified designs

# Adaptive Randomized Experiments

- Start with an initial treatment assignment on a small wave of data
- Repeated cross-sections  $t = 1, \dots, T$  of sample sizes  $N_t$
- Treatment assignment in wave  $t$  depend on earlier outcomes  $(Y_{it-1}^1, \dots, Y_{it-1}^k)$ 
  - ⇒ Rely on algorithms to shift to the best performing arm(s) at each round
  - ⇒ Detect the best-performing treatment more efficiently than static design

# Statistical Analysis of Experiments

- For each randomization design, we'll consider two complementary approaches
  - ① Asymptotic inference
    - ⇒ (semi-) **Parametric** models for the conditional mean of observed outcomes
    - ⇒ **Observed outcomes** vary through random sampling from a population of units
    - ⇒ **Approximate distribution** of the test statistic through large-sample properties
  - ② Randomization inference (aka Fisher's exact  $p$ -values)
    - ⇒ **Nonparametric** (no restrictions on the distribution of the potential outcomes)
    - ⇒ **Treatment assignments** are the sole source of randomness
    - ⇒ Assignment mechanism determines **exact distribution** of the test statistic

## Completely Randomized Experiments

# An Example

Unit	Potential Outcomes				
	Cough Frequency (cfa)		Observed Variables		
	$Y_i(0)$	$Y_i(1)$	$W_i$	$X_i$ (cfp)	$Y_i^{\text{obs}}$ (cfa)
1	?	3	1	4	3
2	?	5	1	6	5
3	?	0	1	4	0
4	4	?	0	4	4
5	0	?	0	1	0
6	1	?	0	5	1

# The Sharp Null

$$H_0 : Y_i(0) = Y_i(1) \quad \forall i = 1, \dots, 6.$$

- One test statistics from example above is

$$\begin{aligned} T(\mathbf{W}, \mathbf{Y}^{\text{obs}}) &= | \bar{Y}_t^{\text{obs}} - \bar{Y}_c^{\text{obs}} | \\ &= | (Y_1^{\text{obs}} + Y_2^{\text{obs}} + Y_3^{\text{obs}})/3 - (Y_4^{\text{obs}} + Y_5^{\text{obs}} + Y_6^{\text{obs}})/3 | \\ &= | 8/3 - 5/3 | = 1.00 \end{aligned}$$

- Under  $H_0$ , all missings in potential outcomes inferred from obs. outcomes

# Treatment Assignments Generate Test Distribution

- We can re-do this for  $\binom{6}{3} = 20$  permutations of treatment assignments
  - ⇒ E.g. instead of  $\mathbf{W}^{\text{obs}} = (1, 1, 1, 0, 0, 0)$  take  $\tilde{\mathbf{W}} = (0, 1, 1, 0, 0, 1)$
  - ⇒ No change in observed outcomes since  $Y_i(0) = Y_i(1) = Y_i^{\text{obs}}$  under  $H_0$
- The value of the test statistic for  $\tilde{W}$  is

$$\begin{aligned} T(\tilde{\mathbf{W}}, \mathbf{Y}^{\text{obs}}) &= |(Y_2^{\text{obs}} + Y_3^{\text{obs}} + Y_6^{\text{obs}})/3 - (Y_1^{\text{obs}} + Y_4^{\text{obs}} + Y_5^{\text{obs}})/3| \\ &= |6/3 - 7/3| = 0.33 \end{aligned}$$

# Treatment Assignments Generate Test Distribution

						Statistic: Absolute Value of Difference in Average	
$W_1$	$W_2$	$W_3$	$W_4$	$W_5$	$W_6$	Levels ( $Y_i$ )	Ranks ( $R_i$ )
0	0	0	1	1	1	-1.00	-0.67
0	0	1	0	1	1	-3.67	-3.00
0	0	1	1	0	1	-1.00	-0.67
0	0	1	1	1	0	-1.67	-1.67
0	1	0	0	1	1	-0.33	0.00
0	1	0	1	0	1	2.33	2.33
0	1	0	1	1	0	1.67	1.33
0	1	1	0	0	1	-0.33	0.00
0	1	1	0	1	0	-1.00	-1.00
0	1	1	1	0	0	1.67	1.33
1	0	0	0	1	1	-1.67	-1.33
1	0	0	1	0	1	1.00	1.00
1	0	0	1	1	0	0.33	0.00
1	0	1	0	0	1	-1.67	-1.33
1	0	1	0	1	0	-2.33	-2.33
1	0	1	1	0	0	0.33	0.00
1	1	0	0	0	1	1.67	1.67
1	1	0	0	1	0	1.00	0.67
1	1	0	1	0	0	3.67	3.00
1	1	1	0	0	0	<b>1.00</b>	<b>0.67</b>

Note: Observed values in boldface ( $R_i$  is rank( $Y_i$ )). Data based on cough frequency for first six units from honey study.

# Computation of Exact $p$ -values

- Calculate the value of the statistic for each assignment vector
- In previous example, each assignment vector has prior probability=1/20
- How unusual is  $T(\mathbf{W}, \mathbf{Y}^{\text{obs}}) = 1.00$  under the sharp null hypothesis?
  - ⇒ There are 16/20 assignments with  $T(\tilde{\mathbf{W}}, \mathbf{Y}^{\text{obs}}) > T(\mathbf{W}, \mathbf{Y}^{\text{obs}})$ :  $p$ -value = 0.80
  - ⇒ In this example, the observed difference could well be due to chance

# Computation of Approximate $p$ -values

- Recall that the number of distinct values of the treatment vector is  $\binom{N_c + N_t}{N_t}$ 
  - For instance, if  $N = 100$  and  $q = 0.5$  then  $\dim(\mathbb{W}^+) = e^{29}$
- We thus need to rely on **numerical approximations** to calculate the  $p$ -value
  - Draw vector  $\mathbf{W}_k$  with  $N - N_t$  zeros and  $N_t$  ones from  $\mathbb{W}^+$
  - Compute  $T^{\text{dif}, k} = T(\mathbf{W}_k, \mathbf{Y}^{\text{obs}}) = |\bar{Y}_t^{\text{obs}} - \bar{Y}_c^{\text{obs}}|$
  - Repeat this process  $K - 1$  times and approximate the  $p$ -value by:

$$\hat{p} = \frac{1}{K} \sum_{k=1}^K \mathbf{1}_{T^{\text{dif}, k} \geq T^{\text{dif}, \text{obs}}}$$

# What is a Reasonable Choice of $K$ ?

Number of Simulations	P-Value	(s.e.)
100	0.010	(0.010)
1,000	0.044	(0.006)
10,000	0.044	(0.002)
100,000	0.042	(0.001)
1,000,000	0.043	(0.000)

*Note:* Statistic is absolute value of difference in average ranks of treated and control cough frequencies. P-value is proportion of draws at least as large as observed statistic.

# The Choice of the Null Hypothesis

- Fisher's sharp null hypothesis  $\neq$  average null hypothesis
  - ⇒ Treat effect is positive for some units and negative for others
  - ⇒ This does not imply that the average null hypothesis is less relevant
- Fisher's approach can accommodate other sharp null hypotheses. E.g.:

$$H_0 : Y_i(1) = Y_i(0) + C_i \quad \forall i = 1, \dots, N$$

⇒ We will focus on the sharp null hypothesis of no effect whatsoever

# Test Statistic

- Test statistic is any scalar function  $T(\mathbf{W}, \mathbf{Y}^{\text{obs}}, \mathbf{X})$  used to find a  $p$ -value
- Not all statistics have same ability to distinguish null and alternative hp
  - ⇒ A statistic has **power** if it takes values that are large when the null is false
  - ⇒ Use only one statistic (specified before seeing the data) and its  $p$ -value

# The Choice of Statistic

- ① Absolute values of the difference in average outcomes

$$T^{\text{dif}} = \left| \bar{Y}_t^{\text{obs}} - \bar{Y}_c^{\text{obs}} \right| = \left| \frac{\sum_{i:W_i=1} Y_i^{\text{obs}}}{N_t} - \frac{\sum_{i:W_i=0} Y_i^{\text{obs}}}{N_c} \right|$$

⇒ Additive treatment effect and distributions of  $Y_i(0)$  and  $Y_i(1)$  have few outliers

- ② Log transform of  $T^{\text{dif}}$

$$T^{\log} = \left| \frac{\sum_{i:W_i=1} \ln(Y_i^{\text{obs}})}{N_t} - \frac{\sum_{i:W_i=0} \ln(Y_i^{\text{obs}})}{N_c} \right|$$

⇒ Multiplicative treatment effect and distributions of  $Y_i(0)$  and  $Y_i(1)$  are skewed

# The Choice of Statistic

## ③ Quantiles

$$T^{\text{median}} = | \text{med}_t(Y_i^{\text{obs}}) - \text{med}_c(Y_i^{\text{obs}}) |$$

⇒ More robust to outliers

## ④ T-Statistics

$$T^{\text{t-stat}} = \left| \frac{\bar{Y}_t^{\text{obs}} - \bar{Y}_c^{\text{obs}}}{\sqrt{\sigma_t^2/N_c + \sigma_c^2/N_t}} \right|$$

⇒ Allows direct comparison with asymptotic student-t (Randomization-t)

# The Choice of Statistic

## ⑤ Rank Statistic

$$T^{\text{rank}} = | \overline{R_t} - \overline{R_c} | = \left| \frac{\sum_{i:W_i=1} R_i}{N_t} - \frac{\sum_{i:W_i=0} R_i}{N_c} \right|$$

$$\Rightarrow R_i = \sum_{j=1}^N \mathbf{1}_{Y_j^{\text{obs}} \leq Y_i^{\text{obs}}} - \frac{N+1}{2} \text{ (without ties in outcomes)}$$

$$\Rightarrow R_i = \sum_{j=1}^N \mathbf{1}_{Y_j^{\text{obs}} \leq Y_i^{\text{obs}}} + \frac{1}{2} \left( 1 + \sum_{j=1}^N \mathbf{1}_{Y_j^{\text{obs}} = Y_i^{\text{obs}}} \right) - \frac{N+1}{2} \text{ (with ties)}$$

## ⑥ The Kolmogorov-Smirnov Statistic

$$T^{\text{ks}} = \sup_y \left| \hat{F}_t(y) - \hat{F}_c(y) \right|$$

$$\Rightarrow \hat{F}_t(y) = 1/N_t \sum_{i:W_i=1} \mathbf{1}_{Y_i^{\text{obs}} \leq y^*} \text{ and } \hat{F}_c(y) = 1/N_c \sum_{i:W_i=0} \mathbf{1}_{Y_i^{\text{obs}} \leq y^*}$$

# Linear Regression with No Covariates

$$Y_i^{\text{obs}} = \alpha + \tau W_i + \epsilon_i$$

- OLS solves

$$(\hat{\tau}^{\text{ols}}, \hat{\alpha}^{\text{ols}}) = \operatorname{argmin} \sum_{i=1}^N (Y_i^{\text{obs}} - \alpha - \tau W_i)^2$$

- Which gives

$$\hat{\tau}^{\text{ols}} = \frac{\sum_{i=1}^N (W_i - \bar{W})(Y_i^{\text{obs}} - \bar{Y}^{\text{obs}})}{\sum_{i=1}^N (W_i - \bar{W})^2}$$

$$\hat{\alpha}^{\text{ols}} = \bar{Y}^{\text{obs}} - \hat{\tau}^{\text{ols}} \bar{W}$$

- Hence

$$\hat{\tau}^{\text{ols}} = \bar{Y}_t^{\text{obs}} - \bar{Y}_c^{\text{obs}}$$

# Asymptotic Inference

- Assuming  $\tau = Y_i(1) - Y_i(0) \forall i$ , the estimated variance of the OLS residuals is

$$\hat{\sigma}_{Y|W}^2 = \frac{1}{N-2} \sum_{i=1}^N \hat{\epsilon}_i^2 = \frac{1}{N-2} \sum_{i=1}^N (Y_i^{\text{obs}} - \hat{Y}_i^{\text{obs}})^2$$

- The estimator for the variance of  $\tau^{\text{ols}}$  is

$$\hat{V}_{\text{homosk}} = \frac{\hat{\sigma}_{Y|W}^2}{\sum_{i=1}^N (W_i - \bar{W})^2} = \hat{\sigma}_{Y|W}^2 \left\{ \frac{1}{N_t} + \frac{1}{N_c} \right\}$$

- Where we have used the fact that  $\sigma_{Y|W}^2 = \sigma_t^2 = \sigma_c^2$  (homoskedasticity)

# Asymptotic Inference

- Estimator for the sampling variance of  $\hat{\tau}^{\text{OLS}}$  that allows for heteroskedasticity

$$\hat{V}_{\text{robust}} = \frac{\sum_{i=1}^N \hat{\epsilon}_i^2 \cdot (W_i - \bar{W})^2}{\left( \sum_{i=1}^N (W_i - \bar{W})^2 \right)^2} = \frac{\hat{\sigma}_t^2}{N_t} + \frac{\hat{\sigma}_c^2}{N_c}$$

- where

$$\hat{\sigma}_t^2 = \frac{1}{N_t - 1} \sum_{i: W_i = 1} (Y_i^{\text{obs}} - \hat{Y}_t^{\text{obs}})^2$$

$$\hat{\sigma}_c^2 = \frac{1}{N_c - 1} \sum_{i: W_i = 0} (Y_i^{\text{obs}} - \hat{Y}_c^{\text{obs}})^2$$

# Linear Regression with Covariates

$$Y_i^{\text{obs}} = \alpha + \tau W_i + \mathbf{X}_i \beta + \epsilon_i$$

- Same as above after conditioning out  $\mathbf{X}_i$

$$\widehat{V}_{\mathbf{X}}^{\text{homosk}} = \frac{\widehat{\sigma}_{Y|W,\mathbf{X}}^2}{\sum_{i=1}^N (W_i - \bar{W})^2} = \widehat{\sigma}_{Y|W,\mathbf{X}}^2 \left\{ \frac{1}{N_t} + \frac{1}{N_c} \right\}$$

$$\widehat{V}_{\mathbf{X}}^{\text{robust}} = \frac{\sum_{i=1}^N \widehat{\epsilon}_{\mathbf{X},i}^2 \cdot (W_i - \bar{W})^2}{\left( \sum_{i=1}^N (W_i - \bar{W})^2 \right)^2}$$

# Testing for Treatment Effects

$$Y_i^{\text{obs}} = \alpha + \tau W_i + \mathbf{X}_i \beta + W_i (\mathbf{X}_i - \bar{\mathbf{X}}) \gamma + \epsilon_i$$

## ① Zero average treatment effect (the “average null”)

$$H_0 : \mathbb{E}[Y_i(1) - Y_i(0) \mid X_i = x] = 0, \forall x$$

- $Q_{\text{zero}} = \begin{pmatrix} \hat{\tau}^{\text{ols}} \\ \hat{\gamma}^{\text{ols}} \end{pmatrix}' \hat{V}_{\tau, \gamma}^{-1} \begin{pmatrix} \hat{\tau}^{\text{ols}} \\ \hat{\gamma}^{\text{ols}} \end{pmatrix}$

## ② Constant average treatment effect

$$H_0 : \mathbb{E}[Y_i(1) - Y_i(0) \mid X_i = x] = \tau, \forall x$$

- $Q_{\text{const}} = \begin{pmatrix} \hat{\gamma}^{\text{ols}} \end{pmatrix}' \hat{V}_{\gamma}^{-1} \hat{\gamma}^{\text{ols}}$

# Testing for Treatment Effects: An Example

**Table 7.3. Regression Estimates for Average Treatment Effects on Post-Cholesterol Levels for the PRC-CPPT Cholesterol Data from Table 7.1**

Covariates	Model for Levels		Model for Logs	
	Est	(s. e.)	Est	(s. e.)
Assignment	-25.04	(2.56)	-0.098	(0.010)
Intercept	-3.28	(12.05)	-0.133	(0.233)
chol1	0.98	(0.04)	-0.133	(0.233)
chol2-chol1	0.61	(0.08)	0.602	(0.073)
chol1 × Assignment	-0.22	(0.09)	-0.154	(0.107)
(chol2-chol1) × Assignment	0.07	(0.14)	0.184	(0.159)
R-squared	0.63		0.57	

**Table 7.4. P-Values for Tests for Constant and Zero Treatment Effects, Using chol1 and chol2-chol1 as Covariates for the PRC-CPPT Cholesterol Data from Table 7.1**

		Post-Cholesterol Level	Compliance
Zero treatment effect	$\chi^2(3)$ approximation	<0.001	<0.001
	Fisher exact p-value	<0.001	0.001
Constant treatment effect	$\chi^2(2)$ approximation	0.029	0.270

# Stratified Randomized Experiments

# What's the Point of Stratification?

- Units grouped according to some **pre-treatment characteristics** into strata
- Rules out **substantial imbalances** in covariates that could arise by chance
- Within each **stratum**, a completely randomized experiment is conducted

# The Benefits of Stratification

- Consider a DGP with  $i = 1, \dots, N$  and one covariate  $G_i \in \{f, m\}$

$$\Rightarrow p(G_i = f) = p = \frac{N(f)}{N}$$

$$\Rightarrow p(G_i = m) = 1 - p = \frac{N(m)}{N}$$

- Completely randomized design

$$\Rightarrow N_t = qN \text{ and } N_c = (1 - q)N$$

- ATE and its sampling variance

$$\hat{\tau}^{\text{dif}} = \bar{Y}_t^{\text{obs}} - \bar{Y}_c^{\text{obs}}$$

$$\mathbb{V}(\hat{\tau}^{\text{dif}}) = \frac{\sigma_t^2}{N_t} + \frac{\sigma_c^2}{N_c}$$

# The Benefits of Stratification

- Stratified design

$$\Rightarrow N_t(f) = pqN \text{ and } N_c(f) = p(1-q)N$$

$$\Rightarrow N_t(m) = (1-p)qN \text{ and } N_c(m) = (1-p)(1-q)N$$

- CATE ( $G_i$ )

$$\hat{\tau}^{\text{dif}}(f) = \bar{Y}_t^{\text{obs}}(f) - \bar{Y}_c^{\text{obs}}(f)$$

$$\hat{\tau}^{\text{dif}}(m) = \bar{Y}_t^{\text{obs}}(m) - \bar{Y}_c^{\text{obs}}(m)$$

- ATE and its sampling variance

$$\hat{\tau}^{\text{strat}} = p\hat{\tau}^{\text{dif}}(f) + (1-p)\hat{\tau}^{\text{dif}}(m)$$

$$\mathbb{V}(\hat{\tau}^{\text{strat}}) = \frac{p}{N} \left( \frac{\sigma_t^2(f)}{p} + \frac{\sigma_c^2(f)}{1-p} \right) + \frac{1-p}{N} \left( \frac{\sigma_t^2(m)}{p} + \frac{\sigma_c^2(m)}{1-p} \right)$$

# The Benefits of Stratification

- The difference in the two variances is

$$\mathbb{V}(\hat{\tau}^{\text{dif}}) - \mathbb{V}(\hat{\tau}^{\text{strat}}) = \frac{p(1-p)}{N}((\mu_c(f) - \mu_c(m))^2 + (\mu_t(f) - \mu_t(m))^2) \geq 0$$

- ⇒ The extra-variance in dif vs. strat comes from the unbalancedness of  $G_i$
- ⇒ In principle,  $\hat{V}^{\text{dif}} < \hat{V}^{\text{strat}}$  (within-stratum potential outcome variances)

# An Alternative to Stratification: Re-randomization

- What if after the random draw some (important) covariates are unbalanced?
- Randomize many times and select the draw that achieves better balance
  - ⇒ E.g. pick the draw with the minimum maximum  $t$ -stat across covariates
- Preferred over stratification if need balance among several variables
- Inference is tricky: not every  $\mathbf{W}$  is ex-post equally probable !
  - ⇒  $p$ -values need to be adjusted for the re-randomization
  - ⇒ Ignoring the adjustment leads to conservative  $p$ -values

# Re-randomization: Example

- $N = 100$  individuals, with 50 women and 50 men
- Completely randomize 60 individuals to treatment
  - ⇒ Reject and re-randomize many times until we get 30 men and 30 women
- This is a stratified experiment
  - ⇒ Need to track the entire sequence of assignment vectors that led to  $\mathbf{W}$

# The Structure of Stratified Randomized Experiments

- Let  $J$  be the number of strata/blocks, and  $N(j), N_c(j), N_t(j)$
- Let  $S_i \in \{1, \dots, J\}$  be the stratum for unit  $i$
- Let  $B_i(j) = \mathbf{1}_{S_i=j}$  be the stratum indicator for unit  $i$
- The assignment mechanism is

$$P(\mathbf{W}|\mathbf{B}, \mathbf{Y}(0), \mathbf{Y}(1)) = \prod_{j=1}^J \binom{N(j)}{N_t(j)}^{-1} \text{ for } \mathbf{W} \in \mathbb{W}^+$$

$$\Rightarrow \mathbb{W}^+ = \{\mathbf{W} \in \mathbb{W} \mid \sum_{i=1}^N B_i(j) \cdot W_i = N_t(j) \text{ for } j = 1, \dots, J\}$$

# Example: Tennessee Project Star

School/ Stratum	No. of Classes	Regular Classes ( $W_i = 0$ )	Small Classes ( $W_i = 1$ )
1	4	-0.197, 0.236	0.165, 0.321
2	4	0.117, 1.190	0.918, -0.202
3	5	-0.496, 0.225	0.341, 0.561, -0.059
4	4	-1.104, -0.956	-0.024, -0.450
5	4	-0.126, 0.106	-0.258, -0.083
6	4	-0.597, -0.495	1.151, 0.707
7	4	0.685, 0.270	0.077, 0.371
8	6	-0.934, -0.633	-0.870, -0.496, -0.444, 0.392
9	4	-0.891, -0.856	-0.568, -1.189
10	4	-0.473, -0.807	-0.727, -0.580
11	4	-0.383, 0.313	-0.533, 0.458
12	5	0.474, 0.140	1.001, 0.102, 0.484
13	4	0.205, 0.296	0.855, 0.509
14	4	0.742, 0.175	0.618, 0.978
15	4	-0.434, -0.293	-0.545, 0.234
16	4	0.355, -0.130	-0.240, -0.150
Average		-0.13	0.09
(S.D.)		(0.56)	(0.61)

# Randomization Inference for Stratified Experiments

- Sharp null hypothesis

$$H_0 : Y_i(1) = Y_i(0) \forall i = 1, 2, \dots, N.$$

- Define average observed outcomes in stratum  $j$  as

$$\bar{Y}_t^{\text{obs}}(j) = \frac{1}{N_t(j)} \sum_{i:S_i=j} W_i Y_i^{\text{obs}}$$

$$\bar{Y}_c^{\text{obs}}(j) = \frac{1}{N_c(j)} \sum_{i:S_i=j} (1 - W_i) Y_i^{\text{obs}}$$

⇒ Strata-level propensity score is

$$e(j) = \frac{N_t(j)}{N(j)}$$

# Test Statistics

- Within-stratum test statistic

$$T^{\text{dif}}(j) = \left| \bar{Y}_t^{\text{obs}}(j) - \bar{Y}_c^{\text{obs}}(j) \right|$$

⇒ Not very informative as we are interested in treatment effects across all strata

- Linear combination of the within-stratum statistics

$$T^{\text{dif}, \lambda_{RSS}} = \left| \sum_{j=1}^J \frac{N_j}{N} \left( \bar{Y}_t^{\text{obs}}(j) - \bar{Y}_c^{\text{obs}}(j) \right) \right|$$

⇒ Need  $e(j)$  to vary across  $j$  for the test to have power over  $T^{\text{dif}}$

# Randomization Inference of the Tennessee Project Star

- $B_i(j), i = 1, \dots, 68$  (class-level data)

$$H_0 : Y_i(1) = Y_i(0) \quad \forall i = 1, 2, \dots, 68.$$

- Total number of possible assignments is  $(6^{13}) \times 10^2 \times 15$ 
  - ⇒ 13 Schools with two classes in each group:  $\binom{4}{2} = 6$
  - ⇒ 2 Schools with three small classes and two regular classes:  $\binom{5}{2} = 10$
  - ⇒ 1 School with four small classes and two regular classes:  $\binom{6}{2} = 15$
- $T^{\text{dif}} = |\bar{Y}_t^{\text{obs}} - \bar{Y}_c^{\text{obs}}| = 0.224$ , with  $p = 0.034$
- $T^{\text{dif}, \lambda_{RSS}} = |\sum_{j=1}^J \frac{N_j}{N} (\bar{Y}_t^{\text{obs}}(j) - \bar{Y}_c^{\text{obs}}(j))| = 0.241$ , with  $p = 0.023$

# Regression Analysis

$$Y_i^{\text{obs}} = \tau W_i + \sum_{j=1}^J \beta(j) B_i(j) + \epsilon_i$$

- Recall that  $B_i(j) = \mathbf{1}(S_i = j)$  is the stratum indicator for unit  $i$
- $\hat{\tau}^{\text{ols}}$  is not a consistent estimator of ATE if  $\tau(j) \neq \tau(j') \forall j \neq j'$

$$WATE = \frac{\sum_{j=1}^J \omega(j) \tau(j)}{\sum_{j=1}^J \omega(j)}$$

- $\omega(j) = \frac{N_j}{N} \frac{N_t(j)}{N(j)} \frac{N(j) - N_t(j)}{N(j)} = q(j)e(j)(1 - e(j))$

# Asymptotic Inference

- The asymptotic variance of the WATE is

$$\mathbb{V}^{\text{strat}} = \frac{\sum_{i=1}^N \epsilon_i^2 \cdot \left( W_i - \sum_{j=1}^J q(j) B_i(j) \right)^2}{\left( \sum_{j=1}^J \omega(j) \right)^2}$$

⇒ Variance weights more those  $\hat{\tau}(j)$  that are more precisely estimated

$$\mathbb{V}^j = \frac{\sigma^2 / N}{q(j)e(j)(1 - e(j))}$$

# Fully-interacted Model

$$Y_i^{\text{obs}} = \tau W_i \frac{B_i(j)}{N(j)/N} + \sum_{j=1}^J \beta(j) B_i(j) + \sum_{j=1}^{J-1} \gamma(j) W_i \left( B_i(j) - B_i(J) \frac{N(j)}{N(J)} \right) + \epsilon_i$$

⇒ In this case,  $\hat{\tau}^{\text{ols}}$  is a consistent estimator of ATE

- With asymptotic variance

$$\mathbb{V}^{\text{strat,inter}} = \sum_{i=1}^N q(j)^2 \cdot \left( \frac{\sigma_c^2(j)}{q(j)(1-e(j))} + \frac{\sigma_t^2(j)}{q(j)e(j)} \right)$$

⇒ In general,  $\mathbb{V}^{\text{strat,inter}} > \mathbb{V}^{\text{strat}}$

# Regression Analysis of the Tennessee Project Star

- The point estimate of  $\tau$  in the standard model is

$$\Rightarrow \hat{\tau}^{\text{ols}} = 0.238 \ (\widehat{s.e.} = 0.103)$$

- The point estimate of  $\tau$  in the fully-interacted model is

$$\Rightarrow \hat{\tau}^{\text{ols,inter}} = 0.241 \ (\widehat{s.e.} = 0.095)$$

- Limited heterogeneity in the treatment effects across strata

# Pairwise Randomized Experiments

# What is a Pairwise Experiment?

- Stratified experiments with exactly two units in each stratum
- Each stratum has the same proportion of treated units
- Standard estimator of sampling variance estimator of ATE not feasible

# Example: Children's Television Workshop Experiment

Pair	Unit A					Unit B				
	$Y_{i,A}(0)$	$Y_{i,A}(1)$	$W_{i,A}$	$Y_{i,A}^{\text{obs}}$	$X_{i,A}$	$Y_{i,B}(0)$	$Y_{i,B}(1)$	$W_{i,B}$	$Y_{i,B}^{\text{obs}}$	$X_{i,B}$
1	54.6	?	0	54.6	12.9	?	60.6	1	60.6	12.0
2	56.5	?	0	56.5	15.1	?	55.5	1	55.5	13.9
3	75.2	?	0	75.2	16.8	?	84.8	1	84.8	17.2
4	76.6	?	0	75.6	15.8	?	101.9	1	101.9	18.9
5	55.3	?	0	55.3	13.9	?	70.6	1	70.6	15.3
6	59.3	?	0	59.3	14.5	?	78.4	1	78.4	16.6
7	87.0	?	0	87.0	17.0	?	84.2	1	84.2	16.0
8	73.7	?	0	73.7	15.8	?	108.6	1	108.6	20.1

# The Structure of Pairwise Randomized Experiments

- The number of units,  $N$ , is even. The **number of strata** is  $J = N/2$
- $N_t(j) = N_c(j) = 1$ , and  $N(j) = 2$  for all  $j = 1, \dots, J$
- The assignment mechanism is

$$P(\mathbf{W}|\mathbf{G}, \mathbf{Y}(0), \mathbf{Y}(1)) = \prod_{j=1}^{N/2} \binom{N(j)}{N_t(j)}^{-1} = \prod_{j=1}^{N/2} \frac{1}{2} = 2^{-N/2}, \text{ for } \mathbf{W} \in \mathbb{W}^+$$

$\Rightarrow \mathbb{W}^+ = \{\mathbf{W} \in \mathbb{W} \mid \sum_{i:G_i=j} W_i = 1, \text{ for } j = 1, \dots, N/2\}$

$\Rightarrow G_i$  is the variable indicating the pair, with  $G_i \in \{1, \dots, N/2\}$

# Potential Outcomes

- For all pairs  $j$ ,  $W_{j,A} = 1 - W_{j,B}$  and  $P(W_{j,A} | \mathbf{Y}(0), \mathbf{Y}(1), \mathbf{X}) = 1/2$

⇒ Potential outcomes are

$$Y_{j,A}^{\text{obs}} = \begin{cases} Y_{j,A}(0) & \text{if } W_{j,A} = 0 \\ Y_{j,A}(1) & \text{if } W_{j,A} = 1 \end{cases}$$

$$Y_{j,B}^{\text{obs}} = \begin{cases} Y_{j,B}(0) & \text{if } W_{j,A} = 1 \\ Y_{j,B}(1) & \text{if } W_{j,A} = 0 \end{cases}$$

# Estimand

- The average treatment effect within pair  $j$  is

$$\begin{aligned}\tau^{\text{pair}}(j) &= \frac{1}{2} \sum_{i:G_i=j} (Y_i(1) - Y_i(0)) \\ &= \frac{1}{2} \{(Y_{j,A}(1) - Y_{j,A}(0)) + (Y_{j,B}(1) - Y_{j,B}(0))\}\end{aligned}$$

⇒ The ATE is

$$\begin{aligned}\tau &= \frac{1}{N} \sum_{i=1}^N (Y_i(1) - Y_i(0)) \\ &= \frac{2}{N} \sum_{j=1}^{N/2} \tau^{\text{pair}}(j)\end{aligned}$$

# Randomization Inference

$$H_0 : Y_i(1) = Y_i(0), \quad \forall i = 1, 2, \dots, N.$$

- Usual “absolute difference” statistic across pairs is

$$\begin{aligned} T^{\text{dif}} &= \left| \frac{1}{J} \sum_{j=1}^J (Y_{j,t}^{\text{obs}} - Y_{j,c}^{\text{obs}}) \right| \\ &= \left| \frac{2}{N} \sum_{j=1}^{N/2} (W_{i,A}(Y_{j,A}^{\text{obs}} - Y_{j,B}^{\text{obs}})(1 - W_{i,A})(Y_{j,B}^{\text{obs}} - Y_{j,A}^{\text{obs}})) \right| \\ &= \left| \bar{Y}_t^{\text{obs}} - \bar{Y}_c^{\text{obs}} \right| \end{aligned}$$

$\Rightarrow \neq p\text{-value}$  than under stratified/completely randomized designs

# Randomization Inference (cont'd)

- Alternative statistics include

$$T^{\text{rank}} = |\bar{R}_t - \bar{R}_c|$$

$$= \left| \frac{2}{N} \sum_{j=1}^{N/2} (W_{i,A} (R_{j,A} - R_{j,B}) + (1 - W_{i,A}) (R_{j,B} - R_{j,A})) \right|$$

$$T^{\text{rank,pair}} = \left| \frac{2}{N} \sum_{j=1}^{N/2} \left( \mathbf{1}_{Y_{j,1}^{\text{obs}} > Y_{j,0}^{\text{obs}}} - \mathbf{1}_{Y_{j,1}^{\text{obs}} < Y_{j,0}^{\text{obs}}} \right) \right|$$

- Both statistics are **robust to the presence of outliers** in observed outcomes
- $T^{\text{rank,pair}}$  has more power than  $T^{\text{rank}}$  when **outcomes vary a lot across pairs**

# Normalized Rank: Children's Television Example

Pair $G_i$	Treatment $W_i$	Pre-Test Score $X_i$	Post-Test Score $Y_i^{\text{obs}}$	Normalized Rank
				Post-Test Score $R_i$
1	0	12.9	54.6	-7.5
1	1	12.0	60.6	2.5
2	0	15.1	56.5	-4.5
2	1	12.3	55.5	5.5
3	0	16.8	75.2	0.5
3	1	17.2	84.8	4.5
4	0	15.8	75.6	1.5
4	1	18.9	101.9	7.5
5	0	13.9	55.3	-6.5
5	1	15.3	70.6	-1.5
6	0	14.5	59.3	-3.5
6	1	16.6	78.4	2.5
7	0	17.0	87.0	5.5
7	1	16.0	84.2	3.5
8	0	15.8	73.7	-0.5
8	1	20.1	108.6	7.5

# Randomization Inference: Children's Television Example

- $T^{\text{dif}} = 13.4$ ,  $p\text{-value} = 0.031$
- $T^{\text{rank}} = 3.8$ ,  $p\text{-value} = 0.031$
- $T^{\text{rank,pair}} = 0.5$ ,  $p\text{-value} = 0.145$

⇒ For the two pairs where  $Y_{j,1}^{\text{obs}} < Y_{j,0}^{\text{obs}}$  the difference in outcomes is small

# Regression Methods

- Within-pair difference in observed outcomes

$$\hat{\tau}^{\text{pair}}(j) = Y_{j,1}^{\text{obs}} - Y_{j,0}^{\text{obs}}$$

- Then consider the following (trivial) regression

$$\hat{\tau}^{\text{pair}}(j) = \tau + \epsilon_j$$

- Estimator for the ATE is the **OLS constant**

$$\hat{\tau}^{\text{ols}} = \frac{2}{N} \sum_{j=1}^{N/2} \hat{\tau}^{\text{pair}}(j)$$

# Regression Methods: Inference

- Within-stratum variance requires at least two treated and two control units
- Assume treatment effect is constant across pairs:  $\tau^{\text{pair}}(j) = \tau$
- Sample variance of pair-level treatment effect estimates

$$\hat{V}^{\text{pair}} = \frac{1}{(N/2)^2} \sum_{j=1}^{N/2} (\hat{\tau}^{\text{pair}}(j) - \hat{\tau})^2$$

⇒ Upwardly biased when there is heterogeneity in the treatment effects

# Regression Methods: Adding Covariates

- Adding covariates as **within-pair difference**

$$\hat{\tau}^{\text{pair}}(j) = \tau + \beta \Delta_{X,j} + \epsilon_j$$

$$\Rightarrow \Delta_{X,j} = (W_{j,A} \cdot (X_{j,A} - X_{j,B}) + (1 - W_{j,A}) \cdot (X_{j,B} - X_{j,A}))$$

- Adding covariates as **within-pair average**

$$\hat{\tau}^{\text{pair}}(j) = \tau + \gamma \overline{X}_j + \epsilon_j$$

$$\Rightarrow \overline{X}_j = (X_{j,A} + X_{j,B}) / 2$$

- General case

$$\hat{\tau}^{\text{pair}}(j) = \tau + \beta \Delta_{X,j} + \gamma (\overline{X}_j - \overline{X}) + \epsilon_j$$

# Regression Methods: Children's Television Example

- For the regression model with only a constant

$$\hat{\tau}^{\text{ols}} = 13.4 \ (\widehat{s.e.} = 4.3)$$

- For the regression function that includes the **within-pair difference**

$$\hat{\tau}^{\text{ols}} = 9.0 \ (\widehat{s.e.} = 1.5) \text{ and } \hat{\beta}^{\text{ols}} = 5.4 \ (\widehat{s.e.} = 0.6)$$

- For the regression function that includes the **within-pair average**

$$\hat{\tau}^{\text{ols}} = 13.4 \ (\widehat{s.e.} = 3.5) \text{ and } \hat{\gamma}^{\text{ols}} = 3.9 \ (\widehat{s.e.} = 1.7)$$

- Including **both terms**

$$\hat{\tau}^{\text{ols}} = 8.5 \ (\widehat{s.e.} = 1.5), \hat{\beta}^{\text{ols}} = 5.9 \ (\widehat{s.e.} = 0.8), \text{ and } \hat{\gamma}^{\text{ols}} = -1.0 \ (\widehat{s.e.} = 0.7)$$

# Clustered Randomized Experiments

# What's the Point of Clustering?

- The population is first partitioned into a number of clusters
- Then all units in a cluster are assigned to the same treatment level
- This design is not efficient
  - ⇒ There may be interference between units at the unit-level violating SUTVA
  - ⇒ In many cases it is easier to sample units at the cluster level

# The Structure of Clustered Experiments

- Let  $G_{ig}$  be a binary indicator that unit  $i$  belongs to cluster  $g = 1, \dots, G$
- $N_g = \sum_{i=1}^N G_{ig}$ , so that  $N_g/N$  is the share of cluster  $g$  in the sample
- $\bar{W}_g \in \{0, 1\}$  is the treatment assignment for all units in cluster  $g$
- The assignment mechanism is

$$P(\mathbf{W}, \mathbf{Y}(0), \mathbf{Y}(1), \mathbf{X}) = \binom{G}{G_t}^{-1}$$

$$\Rightarrow \mathbb{W}^+ = \{\mathbf{W} \in \mathbb{W} \mid \sum_{g=1}^G \bar{W}_g = G_t\}$$

# Example: The *Progresa* Program

- Clustered RCT during the roll-out of the program in rural areas
  - ⇒ 506 villages among those eligible to receive the program
  - ⇒ 320 early treatment and 186 late treatment (control)
- Individual/HH level data for both eligible and non-eligible HHs in each village
  - ⇒ Approx. 30,000 program eligible children
  - ⇒ About 50-100 HHs per village

# Estimands

- The choice of estimand depends on the choice of the unit of analysis
  - ⇒ Unit-level: a natural estimand is the usual ATE

$$\tau = \frac{1}{N} \sum_{i=1}^N (Y_i(1) - Y_i(0))$$

⇒ Cluster-level: weighted average of the unit-level treatment effect

$$\tau^{\text{clust}} = \frac{1}{G} \sum_{g=1}^G \tau_g, \quad \text{where } \tau_g = \frac{1}{N_g} \sum_{i:G_{ig}=1}^N (Y_i(1) - Y_i(0))$$

# Unit-level Vs. Cluster-level

- Cluster-level analysis is more directly linked to the randomization framework
  - ⇒ Differently-sized clusters, such as states or towns
  - ⇒ Many units will be in the same treatment group so unit-level inference is tricky
- Unit-level incorporates individual-level covariates, which improve efficiency
  - ⇒ More homogenous clusters, such as schools or classrooms

# Randomization Inference

- The usual statistic for unit-level analysis

$$T^{\text{dif}} = | \bar{Y}_t^{\text{obs}} - \bar{Y}_c^{\text{obs}} |$$

- The equivalent statistic for cluster-level analysis

$$T^{\text{clust}} = \left| \frac{1}{G_t} \sum_{g: \bar{W}_g=1} \bar{Y}_g^{\text{obs}} - \frac{1}{G_c} \sum_{g: \bar{W}_g=0} \bar{Y}_g^{\text{obs}} \right|$$

# Randomization Inference of *Progresa*

- Children-level analysis on school enrollment (pre-program, placebo)

$$T^{\text{dif}} = 0.0075, \ p\text{-value} = 0.400$$

- Children-level analysis on school enrollment (program year, 1998)

$$T^{\text{dif}} = 0.0388, \ p\text{-value} < 0.001$$

- Village-level analysis on school enrollment (program year, 1998)

$$T^{\text{clust}} = 0.0234, \ p\text{-value} = 0.0120$$

# Regression Methods

- In unit-level analysis, we estimate the following regression

$$Y_i^{\text{obs}} = \alpha + \tau W_i + \bar{X}'\gamma + \epsilon_i$$

$\Rightarrow \hat{\tau}^{\text{ols}}$  consistently estimates ATE (with centered covariates)

- Use Liang-Zeger clustered Var-Cov:

$$\mathbb{V}_{\text{clust}} = \frac{\sum_{g=1}^G \left( \sum_{i: G_{ig}=1} \epsilon_i^2 \cdot (W_i - \bar{W})^2 \right)}{\left( \sum_{i=1}^N (W_i - \bar{W})^2 \right)^2}$$

# Regression Analysis: Cluster-Level

- In cluster-level analysis, consider the following regression

$$\bar{Y}_g^{\text{obs}} = \alpha + \tau \bar{W}_g + \eta_g$$

⇒  $\hat{\tau}^{\text{ols}}$  consistently estimates ATE

- The sampling variance of  $\tau^{\text{ols}}$  is the usual one

$$\mathbb{V} = \frac{\sum_{g=1}^G \eta_g^2}{\sum_{g=1}^G (\bar{W}_g - \bar{W})^2} = \sigma^2 \left\{ \frac{1}{G_t} + \frac{1}{G_c} \right\}$$

# Regression Analysis of *Progresa*

- Children-level analysis on school enrollment (pre-program, placebo)

$$\hat{\tau}^{\text{ols}} = 0.0075 \ (\widehat{s.e.} = 0.0091)$$

- Children-level analysis on school enrollment (program year, 1998)

$$\hat{\tau}^{\text{ols}} = 0.0388 \ (\widehat{s.e.} = 0.0104)$$

- Village-level analysis on school enrollment (program year, 1998)

$$\hat{\tau}^{\text{ols}} = 0.0234 \ (\widehat{s.e.} = 0.0092)$$

# Adaptive Randomized Experiments

# What is an Adaptive Randomized Experiment?

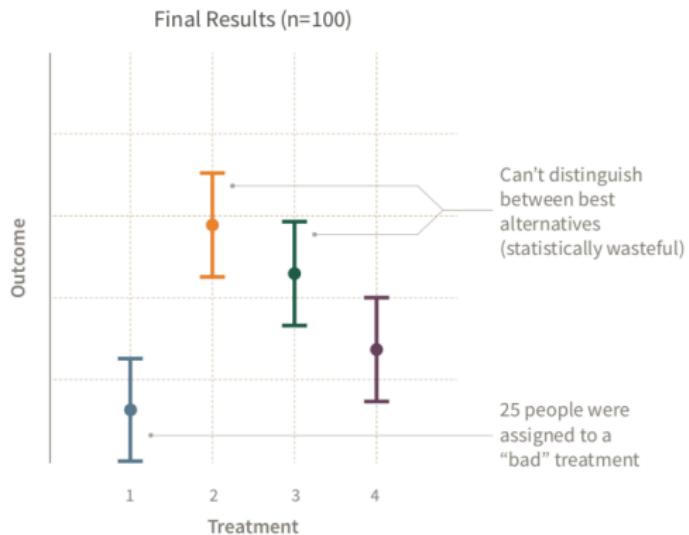
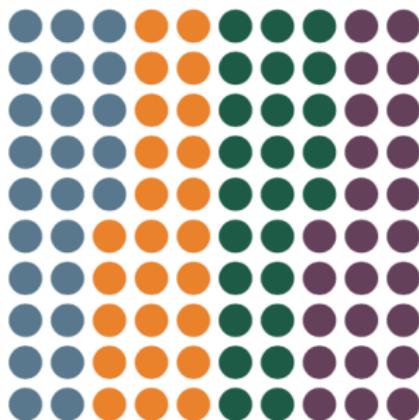
- A standard RCT applies the same procedures for allocating treatments throughout the trial
  - ⇒ An adaptive design may, based on interim analysis of the trial's result, change the allocation of subjects to treatment arms
- Adaptive designs require multiple periods of treatment and outcome assessment
  - ⇒ Well suited to survey, on-line, and lab experiments, where participants are treated and outcomes measured in batches over time
  - ⇒ Some field experiments are conducted in stages (e.g. treatment is to be deployed over time in a series of different regions)

# Illustrative Example

- The goal is to select an optimal website design
  - The treatments are different color schemes
  - The outcome is some measure of visitors' engagement with the website
- In a non-adaptive experiment, we assign each visitor to a particular color scheme and then measure how much she engages with the website
- In an adaptive experiment, we begin with an initial treatment assignment on a small wave of data
  - ⇒ Intermediate results give us some idea of the performance of each arm
  - ⇒ This informs how the next wave of data should be allocated across arms

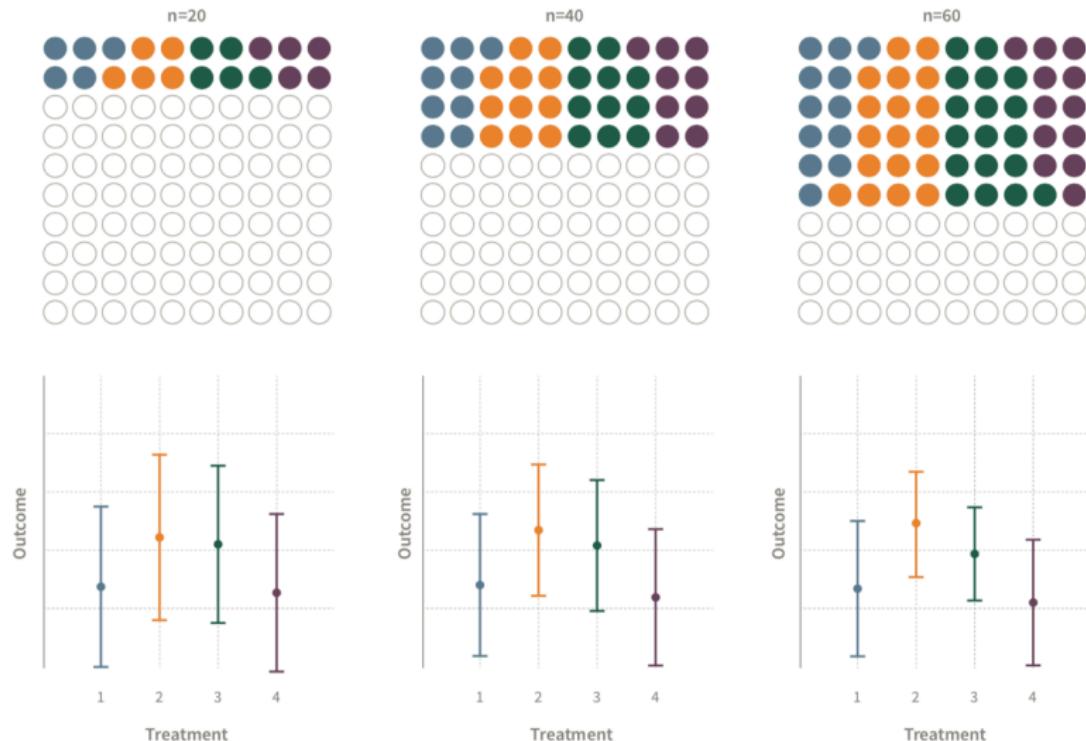
## Illustrative Example (cont'd)

- The fraction of observations (number of users) assigned to each treatment is set before the experiment starts



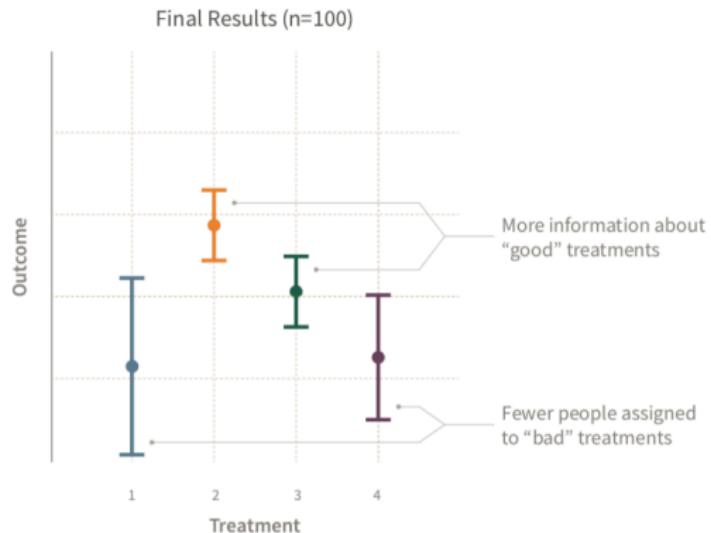
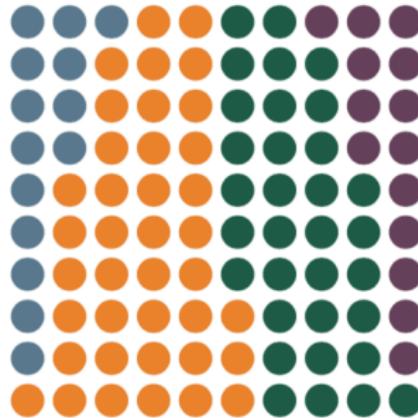
## Illustrative Example (cont'd)

⇒ Each wave re-assigns treatment shares based on intermediate results



## Illustrative Example (cont'd)

- ⇒ We assign the arms that seem more promising more often, according to the objective we set out



# Setup

- Waves  $t = 1, \dots, T$ , sample sizes  $N_t$
  - Treatment  $D \in \{1, \dots, k\}$ , outcomes  $Y \in [0, 1]$ , covariates  $X$
  - Potential outcomes  $Y^d$ , and  $\theta^{dx} = E[Y_{it}^d | X_{it} = x]$
  - Repeated cross-sections:  $(Y_{it}^1, \dots, Y_{it}^k; X_{it})$  are i.i.d. across both  $i$  and  $t$
  - Given all information available at time  $t$  form posterior beliefs  $P_t$  over  $\theta$
- ⇒ Based on beliefs and the objective, decide what share  $p_t^{dx}$  of stratum  $x$  will be assigned to treatment  $d$  in time  $t$

# Thompson Sampling

- In each period subjects are assigned to treatment arms in proportion to the posterior probability that a given arm is best

$$p_t^{dx} = P_t \left( d = \operatorname{argmax}_{d'} \theta^{d'x} \right)$$

- Suppose you care about both participant welfare, and precise point estimates/high power for all treatments

$$\tilde{p}_t^{dx} = (1 - \gamma)p_t^{dx} + \gamma/k$$

⇒ The designer max participant welfare while learning something about the effectiveness of suboptimal treatments

# Exploration Sampling

- Kasy and Sautmann (ECMA, 2021) propose a modification of Thompson sampling probabilities to make them less aggressive
  - ⇒ Increase the expected value of the arm selected at the end of the experiment
- Assigns shares  $q_t^d$  of each wave to treatment  $d$ , where

$$q_t^d = S_t \cdot p_t^d \cdot (1 - p_t^d)$$

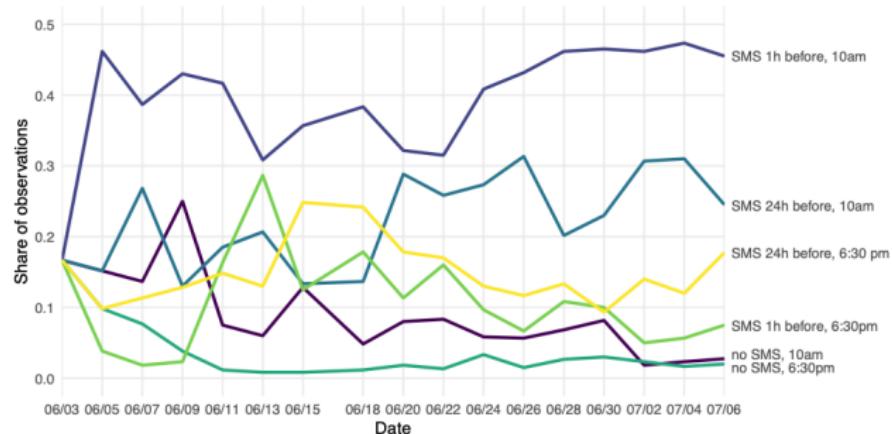
$$p_t^d = P_t \left( d = \operatorname{argmax}_{d'} \theta^{d'} \right)$$

$$S_t = \frac{1}{\sum_d p_t^d (1 - p_t^d)}$$

- ⇒ Shifts weight away from best performing treatment to its close competitors

# Exploration Sampling in Practice

- Kasy and Sautmann (2021) design an experiment using exploration sampling on agricultural extension services for farmers in India
- Six treatments to incentivize phone-call completion
- Outcome is call completion (1=answer five questions asked during the call)
- Daily waves of 600 phone calls randomly selected out of 10,000 valid numbers



# Inference

- Inference has to take into account adaptivity. Example:
- Flip a fair coin
- If head, flip again, else stop
- Probability distribution: 50% tail-stop, 25% head-tail, 25% head-head
- Expected share of heads?

$$0.5 \times 0 + 0.25 \times 0.5 + 0.25 \times 1 = 0.375 \neq 0.5$$

⇒ Sample averages by treatment arms are, in general, biased

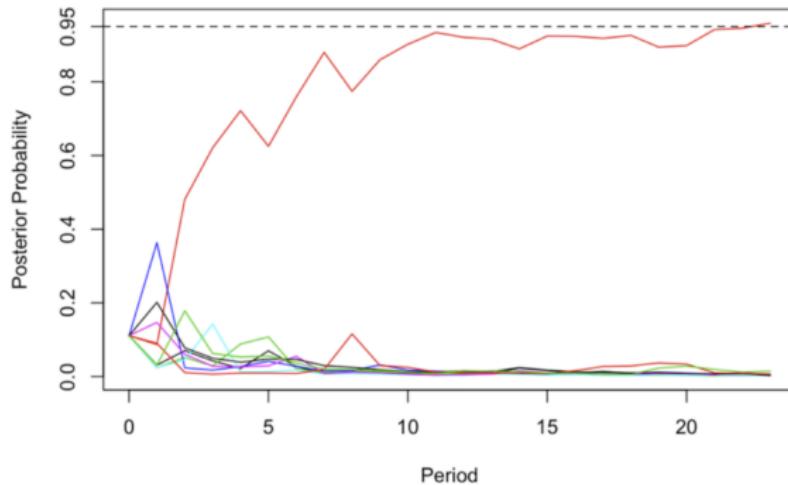
# Randomization inference for Adaptive Designs

- Sharp null hypothesis:  $Y_i^1 = \dots = Y_i^k$
  - Under this null, it is easy to re-simulate the treatment assignment: just let your assignment algorithm run with the data, switching out the treatments
  - Do this many times, re-calculate the test statistic each time
  - Take the  $1 - \alpha$  quantile across simulations as critical value
- ⇒ This delivers finite-sample exact inference for any adaptive assignment scheme

# A Simple Illustration

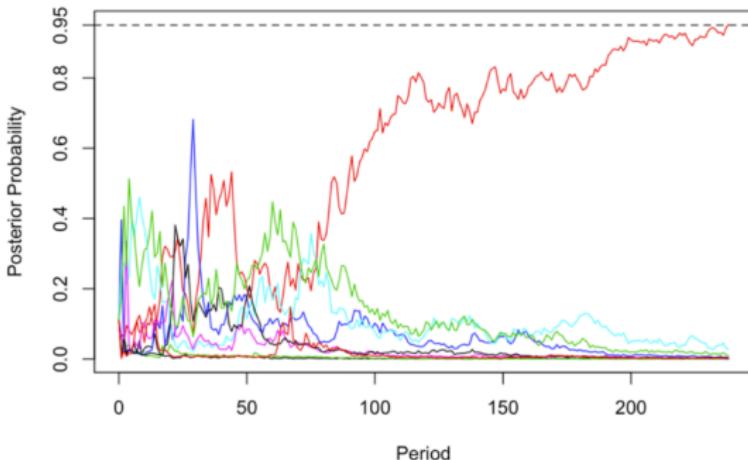
- We simulate an RCT involving a control group and eight treatment arms
- We administer treatments and outcomes for 100 subjects during each period
- The simulation assumes that each subject's outcome is binary (e.g., good versus bad)
- We allocate next period's subjects according to posterior probabilities that a given treatment arm is best
- The stopping rule is that the RCT is halted when one arm is found to have a 95% posterior probability of being best

## A Simple Illustration (cont'd)



- The simulation assumes that the probability of success is 0.10 for all arms except one, which is 0.20
- The best arm (the red line) is correctly identified, and the trial is halted after 23 periods (total N=2300)

## A Simple Illustration (cont'd)



- All but one of the arms have a 0.10 probability of success, and the superior arm has a 0.12 probability of success
- The design eventually settles on the truly superior arm but only after more than 200 periods ( $N=23,810$ )

# Wrapping Up on Adaptive Design

- Funders and implementation partners may welcome the idea of an experimental design that responds to on-the-ground conditions such that problematic arms are scaled back
- ⇒ Even when one arm is clearly superior (inferior), the lead-time necessary to staff or outfit this arm may make it difficult to scale it up (down)
- Adaptive designs add to the complexity of the research design, the implementation and field work, and the ex-post analysis