

Session IV

Practical Issues

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1 Practical Issues

- Participant Recruitment
- Attention, Satisficing, and Noncompliance
- Use of Covariates
- Effect Heterogeneity

2 Handling “Broken” Experiments

3 Research Ethics

4 Conclusion

1 Practical Issues

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1 Practical Issues

■ Participant Recruitment

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How do we find participants?

- Volunteers
 - Volunteer Science
 - In-house subject pool
- Paid crowdworkers
 - Prolific Academic
 - Mechanical Turk
 - Crowdflower
- “Representative” samples
 - Big players: YouGov, TNS, Gallup, Nielsen, GfK
 - Others: Kantar, SSI, Lucid

SUTO Framework

- Cronbach (1986) talks about generalizability in terms of UTO
- Shadish, Cook, and Campbell (2001) speak similarly of:
 - **S**ettings
 - **U**nits
 - **T**reatments
 - **O**utcomes
- External validity depends on all of these

Population

- Setting
- Units
- Treatments
- Outcomes

Your Study

- Setting
- Units
- Treatments
- Outcomes

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In your study, how do these correspond?

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In your study, how do these correspond?
how do these differ?

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In your study, how do these correspond?
how do these differ?
do these differences matter?

Common Differences

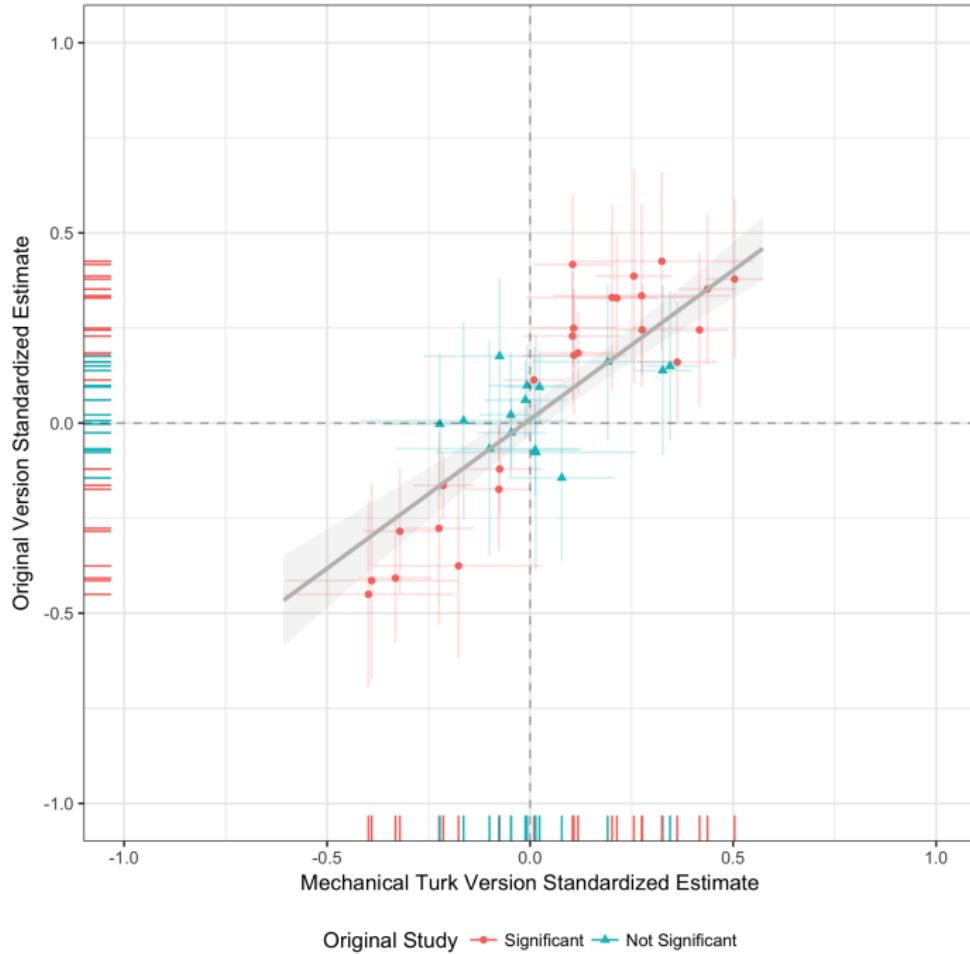
- Most common thing to focus on is demographic representativeness
 - Sears (1986): “students aren’t real people”
 - Western, educated, industrialized, rich, democratic (WEIRD) psychology participants

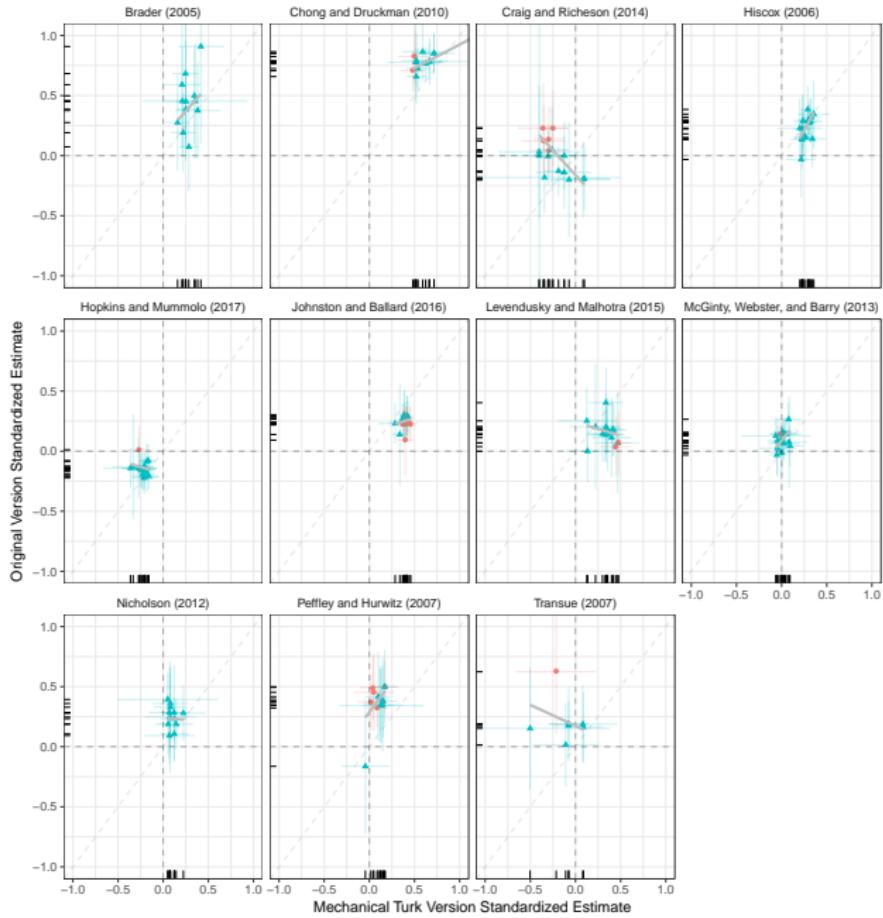
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- But do those characteristics actually matter?
- Shadish, Cook, and Campbell tell us to think about:
 - Surface similarities
 - Ruling out irrelevancies
 - Making discriminations
 - Interpolation/extrapolation





Questions?

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One final issue with unit-related sources of heterogeneity is how we handle or analyze survey-experimental data where we think participants misbehaved.

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This falls into a couple of broad categories:

- Noncompliance
- Inattention
- Survey Satisficing

How should we deal with respondents that appear to not be paying attention, not “taking” the treatment, or not responding to outcome measures?

- 1 Keep them
- 2 Throw them away

Best Practice: Pre-Analysis Protocol

- Excluding respondents based on survey behavior is one of the easiest ways to “p-hack” an experimental dataset
 - Inattention, satisficing, etc. will tend to reduce the size of the SATE
- So regardless of how you handle these respondents, these should be decisions that are made *pre-analysis*

When are you excluding participants?

Pre-Treatment

Post-Treatment

When are you excluding participants?

Pre-Treatment

- Satisficing behaviors

Post-Treatment

When are you excluding participants?

Pre-Treatment

- Satisficing behaviors
- Inattention

Post-Treatment

When are you excluding participants?

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- Satisficing behaviors
- Inattention
- Covariate-based selection

Post-Treatment

When are you excluding participants?

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Post-Treatment

- Speeding on treatment

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Post-Treatment

- Speeding on treatment
- “Failing” a manipulation check

When are you excluding participants?

Pre-Treatment

- Satisficing behaviors
- Inattention
- Covariate-based selection
- Pretreated

Post-Treatment

- Speeding on treatment
- “Failing” a manipulation check
- Drop-off

Pre-Treatment Exclusion

- This is totally fine from a causal inference perspective

Pre-Treatment Exclusion

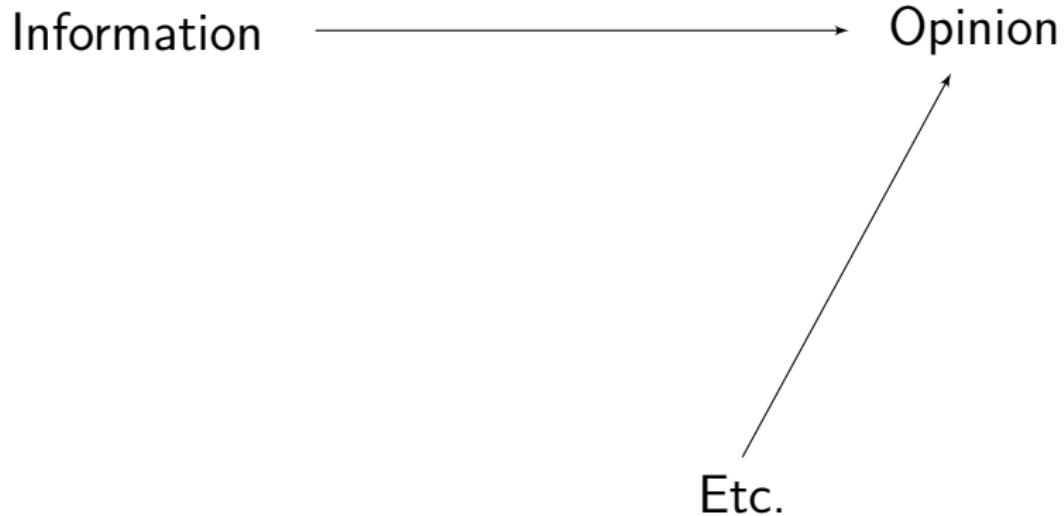
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- Advantages:
 - Focused on engaged respondents
 - Likely increase impact of treatment

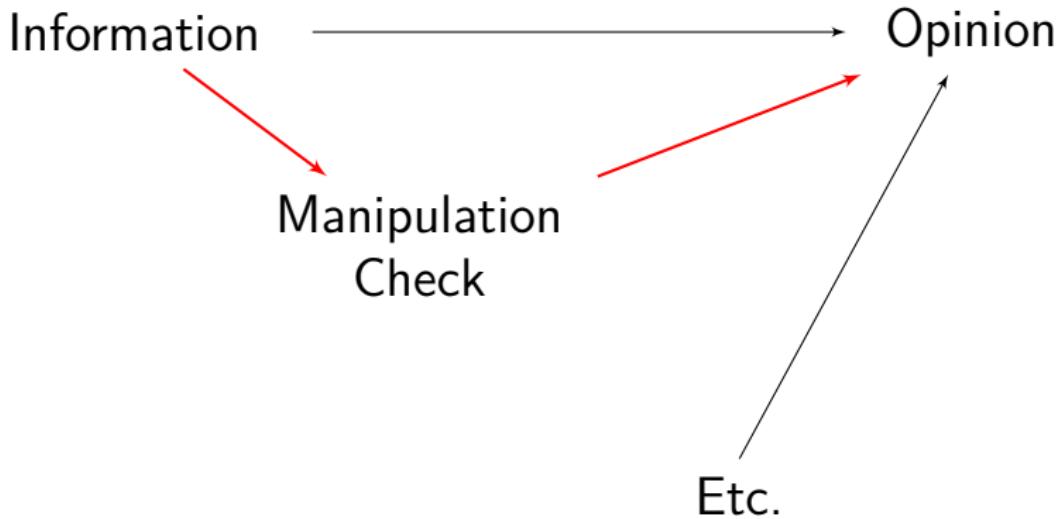
Pre-Treatment Exclusion

- This is totally fine from a causal inference perspective
- Advantages:
 - Focused on engaged respondents
 - Likely increase impact of treatment
- Disadvantages:
 - Changing definition of sample (and thus population)

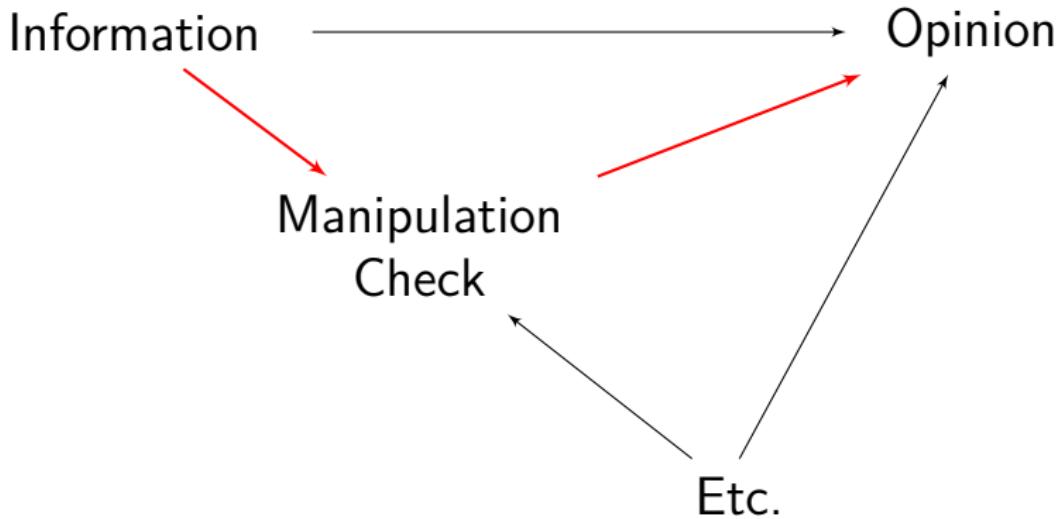
Post-Treatment Exclusion

This is much more problematic because it involves controlling for a *post-treatment* variable





Risk that estimate of β_1 is diminished because effect is being carried through the manipulation check.



Introduction of “collider bias” wherein values of the manipulation check are affected by other factors.

Post-Treatment Exclusion

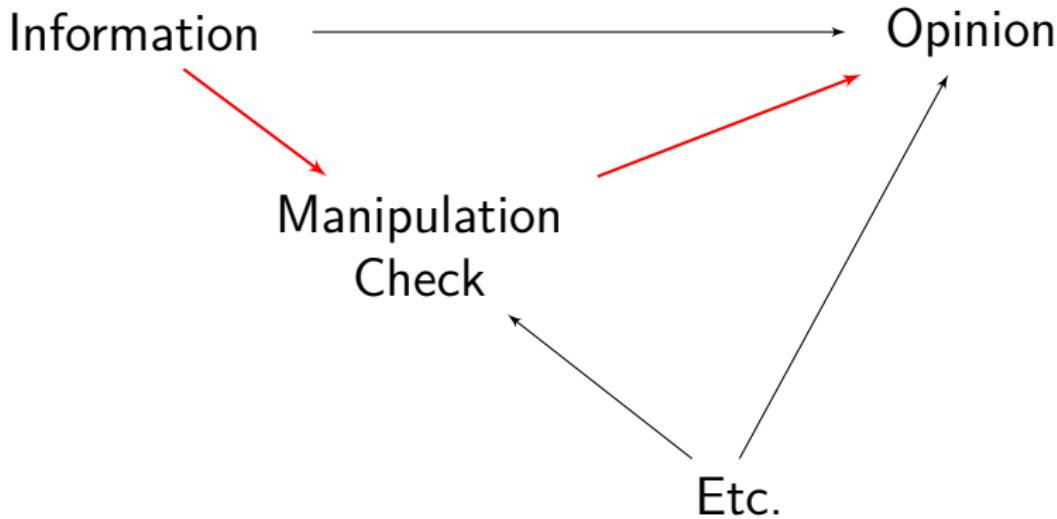
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 - Not problematic if MCAR
 - Nothing really to be done if caused by treatment



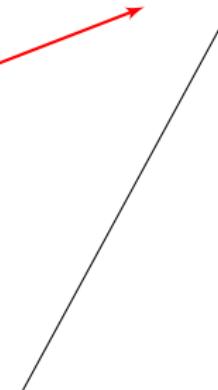
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Information

Opinion

Manipulation
Check

Etc.



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Questions?

Apparent Satisficing

- Some common measures:
 - “Straightlining”
 - Non-differentiation
 - Acquiescence
 - Nonresponse
 - DK responding
 - Speeding
- Difficult to detect and distinguish from “real” responses

Metadata/Paradata

■ Timing

- Some survey tools will allow you to time page
- Make a prior rules about dropping participants for speeding

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■ Mousetracking or eyetracking

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■ Record focus/blur browser events

Direct Measures

- How closely have you been paying attention to what the questions on this survey actually mean?

Direct Measures

- How closely have you been paying attention to what the questions on this survey actually mean?
- While taking this survey, did you engage in any of the following behaviors? Please check all that apply.
 - Use your mobile phone
 - Browse the internet
 - ...

Instructional Manipulation Check

We would like to know if you are reading the questions on this survey. If you are reading carefully, please ignore this question, do not select any answer below, and click “next” to proceed with the survey.

Strongly disagree

Somewhat disagree

Neither agree nor disagree

Somewhat agree

Strongly agree

Instructional Manipulation Check

Do you agree or disagree with the decision to send British forces to fight ISIL in Syria? We would like to know if you are reading the questions on this survey. If you are reading carefully, please ignore this question, do not select any answer below, and click “next” to proceed with the survey.

Strongly disagree

Somewhat disagree

Neither agree nor disagree

Somewhat agree

Strongly agree

[Return](#)

Treatment Noncompliance

■ Definition:

“when subjects who were assigned to receive the treatment go untreated or when subjects assigned to the control group are treated”¹

¹Gerber & Green. 2012. *Field Experiments*, p.132.

Treatment Noncompliance

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“when subjects who were assigned to receive the treatment go untreated or when subjects assigned to the control group are treated” ¹

■ Several strategies

- “As treated” analysis
- “Intention to treat” analysis
- Estimate a LATE

¹Gerber & Green. 2012. *Field Experiments*, p.132.

Analyzing Noncompliance

- If noncompliance only occurs in one group, it is *asymmetric* or *one-sided*
- We can ignore non-compliance and analyze the “intention to treat” effect, which will underestimate our effects because some people were not treated as assigned: $ITT = \bar{Y}_1 - \bar{Y}_0$

Analyzing Noncompliance

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- We can ignore non-compliance and analyze the “intention to treat” effect, which will underestimate our effects because some people were not treated as assigned: $ITT = \bar{Y}_1 - \bar{Y}_0$
- We can use “instrumental variables” to estimate the “local average treatment effect” (LATE) for those that complied with treatment: $LATE = \frac{ITT}{\%Compliant}$

Local Average Treatment Effect

- IV estimate is *local* to the variation in X that is due to variation in D
- This matters if effects are *heterogeneous*
- LATE is effect for those who *comply*
- Four subpopulations:
 - Compliers: $X = 1$ only if $D = 1$
 - Always-takers: $X = 1$ regardless of D
 - Never-takers: $X = 0$ regardless of D
 - Defiers: $X = 1$ only if $D = 0$
- Exclusion restriction! Monotonicity!

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Discussion

Consider the following:

- When **are we required to** include covariates in the analysis of an experiment?
- When **are we allowed to** include covariates in the analysis of an experiment?
- When **are we not allowed to** include covariates in the analysis of an experiment?

Discuss with a partner for 2 minutes.

- We never have to use covariates!

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- We may want to for:
 - Subgroup comparisons
 - Repeated/panel designs
 - In case of noncompliance or attrition

- We never have to use covariates!
- We may want to for:
 - Subgroup comparisons
 - Repeated/panel designs
 - In case of noncompliance or attrition
- Any use of covariates should be planned!

Block Randomization I

Stratification:Sampling::Blocking:Experiments

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- Basic idea: randomization occurs within strata defined before treatment assignment

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Stratification:Sampling::Blocking:Experiments

- Basic idea: randomization occurs within strata defined before treatment assignment
- CATE is estimate for each stratum; aggregated to SATE
- Why?
 - Eliminate chance imbalances
 - Optimized for estimating CATEs
 - More precise SATE estimate

Exp.	Control				Treatment			
1	M	M	M	M	F	F	F	F
2	M	M	M	F	M	F	F	F
3	M	M	F	F	M	M	F	F
4	M	F	F	F	M	M	M	F
5	F	F	F	F	M	M	M	M

```
# population of men and women
pop <- rep(c("Male", "Female"), each = 4)

# randomly assign into treatment and control
split(sample(pop, 8, FALSE), c(rep(0,4), rep(1,4)))
```

Obs.	X_{1i}	X_{2i}	D_i
1	Male	Old	0
2	Male	Old	1
3	Male	Young	1
4	Male	Young	0
5	Female	Old	1
6	Female	Old	0
7	Female	Young	0
8	Female	Young	1

Block Randomization II

- Blocking ensures ignorability of all covariates used to construct the blocks
- Incorporates covariates explicitly into the *design*

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 - Most valuable in small samples

Block Randomization II

- Blocking ensures ignorability of all covariates used to construct the blocks
- Incorporates covariates explicitly into the *design*
- When is blocking *statistically* useful?
 - If those covariates affect values of potential outcomes, blocking reduces the variance of the SATE
 - Most valuable in small samples
 - Not valuable if all blocks have similar potential outcomes

Statistical Properties I

Complete randomization:

$$SATE = \frac{1}{n_1} \sum Y_{1i} - \frac{1}{n_0} \sum Y_{0i}$$

Block randomization:

$$SATE_{blocked} = \sum_1^J \left(\frac{n_j}{n} \right) (\widehat{CATE}_j)$$

Obs.	X_{1i}	X_{2i}	D_i	Y_i	CATE
1	Male	Old	0	5	
2	Male	Old	1	10	
3	Male	Young	1	4	
4	Male	Young	0	1	
5	Female	Old	1	6	
6	Female	Old	0	2	
7	Female	Young	0	6	
8	Female	Young	1	9	

Obs.	X_{1i}	X_{2i}	D_i	Y_i	CATE
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SATE Estimation

$$\begin{aligned} SATE &= \left(\frac{2}{8} * 5\right) + \left(\frac{2}{8} * 3\right) + \left(\frac{2}{8} * 4\right) + \left(\frac{2}{8} * 3\right) \\ &= 3.75 \end{aligned}$$

SATE Estimation

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The blocked and unblocked estimates are the same here because $Pr(Treatment)$ is constant across blocks and blocks are all the same size.

SATE Estimation

- We can use weighted regression to estimate this in an OLS framework
- Weights are the inverse prob. of being treated w/in block
 - $\text{Pr}(\text{Treated}) \text{ by block: } p_{ij} = \text{Pr}(D_i = 1 | J = j)$
 - Weight (Treated): $w_{ij} = \frac{1}{p_{ij}}$
 - Weight (Control): $w_{ij} = \frac{1}{1 - p_{ij}}$

Statistical Properties II

Complete randomization:

$$\widehat{SE}_{SATE} = \sqrt{\frac{\widehat{Var}(Y_0)}{n_0} + \frac{\widehat{Var}(Y_1)}{n_1}}$$

Block randomization:

$$\widehat{SE}_{SATE_{blocked}} = \sqrt{\sum_1^J \left(\frac{n_j}{n}\right)^2 \widehat{Var}(SATE_j)}$$

Statistical Properties II

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Block randomization:

$$\widehat{SE}_{SATE_{blocked}} = \sqrt{\sum_1^J \left(\frac{n_j}{n}\right)^2 \widehat{Var}(SATE_j)}$$

When is the blocked design more efficient?

Practicalities

- Blocked randomization only works in exactly the same situations where stratified sampling works
 - Need to observe covariates pre-treatment in order to block on them
 - Work best in a panel context
- In a single cross-sectional design that might be challenging
 - Some software can block “on the fly”

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Detecting Effect Heterogeneity

Always block if you expect heterogeneity!

- QQ-plots: Suggestive evidence
- Regression using treatment-by-covariate interactions

Detecting Effect Heterogeneity

Always block if you expect heterogeneity!

- QQ-plots: Suggestive evidence
- Regression using treatment-by-covariate interactions
- (Replication and meta-analysis)

Suggestive Evidence

We can never know $\text{Var}(TE_i)$!

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We can never know $\text{Var}(TE_i)$! But . . .

- Quantile-quantile plots

Suggestive Evidence

We can never know $\text{Var}(TE_i)$! But...

- Quantile-quantile plots

- Compare the distribution of Y_0 's to distribution of Y_1 's
- If homogeneity, a vertical shift in Y_1 's
- If heterogeneity, a slope $\neq 1$

Suggestive Evidence

We can never know $\text{Var}(TE_i)$! But...

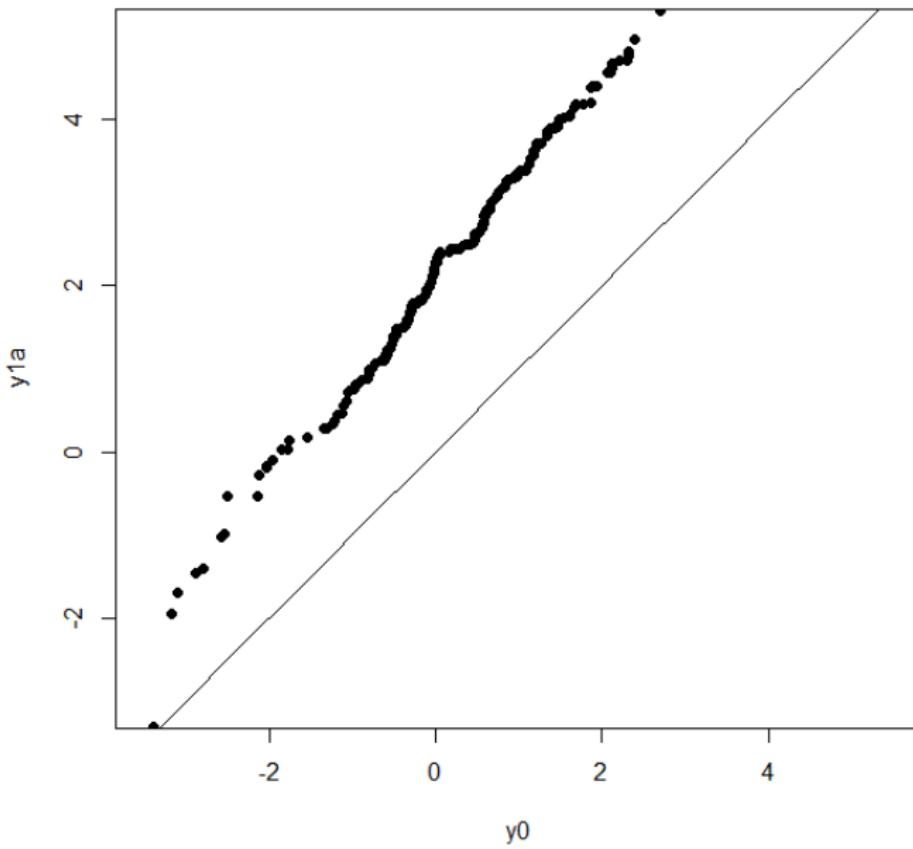
- Quantile-quantile plots
 - Compare the distribution of Y_0 's to distribution of Y_1 's
 - If homogeneity, a vertical shift in Y_1 's
 - If heterogeneity, a slope $\neq 1$
- Equality of variance tests
 - If homogeneity, variance should be equal
 - If heterogeneity, variances should differ

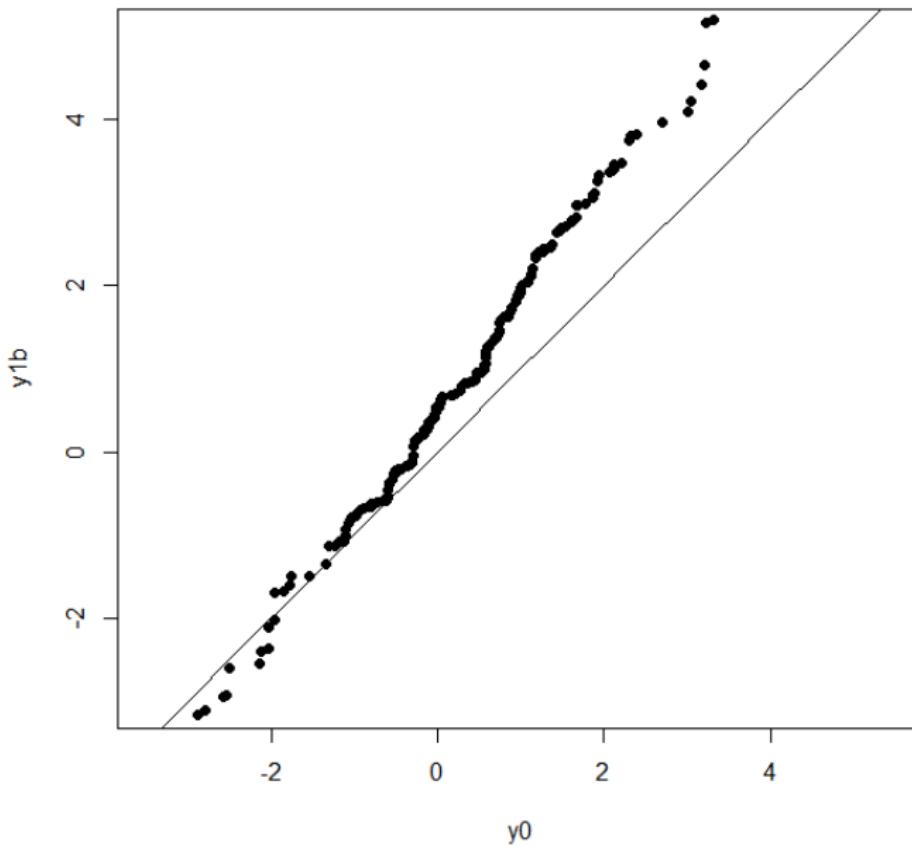
QQ Plots

```
# y_0 data
set.seed(1)
n <- 200
y0 <- rnorm(n) + rnorm(n, 0.2)

# y_1 data (homogeneous effects)
y1a <- y0 + 2 + rnorm(n, 0.2)
# y_1 data (heterogeneous effects)
y1b <- y0 + rep(0:1, each = n/2) + rnorm(n, 0.2)

qqplot(y0, y1a, pch=19, xlim=c(-3,5), ylim=c(-3,5), asp=1)
curve((x), add = TRUE)
qqplot(y0, y1b, pch=19, xlim=c(-3,5), ylim=c(-3,5), asp=1)
curve((x), add = TRUE)
```





Equality of Variance tests

```
> var.test(y0, y1a)
```

F test to compare two variances

data: y0 and y1a

F = 0.60121, num df = 199, denom df = 199,

p-value = 0.0003635

alternative hypothesis:

true ratio of variances is not equal to 1

95 percent confidence interval:

0.4549900 0.7944289

sample estimates:

ratio of variances

0.6012131

Equality of Variance tests

```
> var.test(y0, y1b)
```

F test to compare two variances

data: y0 and y1b

F = 0.53483, num df = 199, denom df = 199,
p-value = 1.224e-05

alternative hypothesis:

true ratio of variances is not equal to 1

95 percent confidence interval:

0.4047531 0.7067133

sample estimates:

ratio of variances

0.5348312

Questions?

Regression Estimation

Aside: Regression Adjustment in Experiments, Generally

- Recall the general advice that we do not need covariates in the regression to “control” for omitted variables (because there are none)
- Including covariates can reduce variance of our SATE by explaining more of the variation in Y

Scenario

Imagine two regression models. Which is correct?

- 1 Mean-difference estimate of SATE is “not significant”
- 2 Regression estimate of SATE, controlling for sex, age, and education, is “significant”

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Imagine two regression models. Which is correct?

- 1 Mean-difference estimate of SATE is “not significant”
- 2 Regression estimate of SATE, controlling for sex, age, and education, is “significant”

This is a small-sample dynamic, so make these decisions pre-analysis!

Treatment-Covariate Interactions

- The regression paradigm allows us to estimate CATEs using interaction terms
 - X is an indicator for treatment
 - M is an indicator for possible moderator

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- CATEs:

$$Y = \beta_0 + \beta_1 X + \beta_2 M + \beta_3 X * M + e$$

Treatment-Covariate Interactions

- The regression paradigm allows us to estimate CATEs using interaction terms
 - X is an indicator for treatment
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- SATE: $Y = \beta_0 + \beta_1 X + e$
- CATEs:

$$Y = \beta_0 + \beta_1 X + \beta_2 M + \beta_3 X * M + e$$

- Homogeneity: $\beta_3 = 0$
- Heterogeneity: $\beta_3 \neq 0$

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Quiz time!

Compliance

1 What is compliance?

Compliance

- 1 What is compliance?
- 2 How can we analyze experimental data when there is noncompliance?

Balance testing

- 1 What does randomization ensure about the composition of treatment groups?

Balance testing

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- 2 What can we do if we find a covariate imbalance between groups?

Balance testing

- 1 What does randomization ensure about the composition of treatment groups?
- 2 What can we do if we find a covariate imbalance between groups?
- 3 How can we avoid this problem entirely?

Nonresponse and Attrition

- 1 Do we care about outcome nonresponse in experiments?

Nonresponse and Attrition

- 1 Do we care about outcome nonresponse in experiments?
- 2 How can we analyze experimental data when there is outcome nonresponse or post-treatment attrition?

Manipulation checks

- 1 What is a manipulation check? What can we do with it?

Manipulation checks

- 1 What is a manipulation check? What can we do with it?
- 2 What do we do if some respondents “fail” a manipulation check?

Null effects

- 1 What should we do if we find our estimated $\widehat{SATE} = 0$?

Null effects

- 1 What should we do if we find our estimated $\widehat{SATE} = 0$?
- 2 What does it mean for an experiment to be *underpowered*?

Null effects

- 1 What should we do if we find our estimated $\widehat{SATE} = 0$?
- 2 What does it mean for an experiment to be *underpowered*?
- 3 What can we do to reduce the probability of obtaining an (unwanted) “null effect”?

Effect heterogeneity

- 1 What should we do if, post-hoc, we find evidence of effect heterogeneity?

Effect heterogeneity

- 1 What should we do if, post-hoc, we find evidence of effect heterogeneity?
- 2 What can we do pre-implementation to address possible heterogeneity?

Representativeness

- 1 Under what conditions is a design-based, probability sample necessary for experimental inference?

Representativeness

- 1 Under what conditions is a design-based, probability sample necessary for experimental inference?
- 2 What kind of causal inferences can we draw from an experiment on a descriptively unrepresentative sample?

Peer Review

- 1 What should we do if a peer reviewer asks us to “control” for covariates in the analysis?

Peer Review

- 1 What should we do if a peer reviewer asks us to “control” for covariates in the analysis?
- 2 What should we do if a peer reviewer asks us to include or exclude particular respondents from the analysis?

Questions?

1 Practical Issues

- Participant Recruitment
- Attention, Satisficing, and Noncompliance
- Use of Covariates
- Effect Heterogeneity

2 Handling “Broken” Experiments

3 Research Ethics

4 Conclusion

History: Key Moments

- 1 Tuskegee (1932-1972) and Guatemala (1946-1948)
Studies
- 2 Nuremberg Code (1947)
- 3 Helsinki Declaration (1964)
- 4 U.S. 45 CFR 46 (1974) and “Common Rule” (1991)
- 5 The Belmont Report (1979)
- 6 EU Data Protection Directive (1995; 2012)
 - UK Data Protection Act (1998)

Helsinki Declaration

- Adopted by the World Medical Association in 1964²
- Narrowly focused on medical research
- Expanded the Nuremberg Code
 - Relaxed consent requirements
 - Risks should not exceed benefits
 - Institutionalization of ethics oversight

²<http://www.bmjjournals.org/content/2/5402/177>

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 - Risks should not exceed benefits
 - Institutionalization of ethics oversight
- Do these rules apply to non-medical research?

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The Belmont Report

- Commissioned by the U.S. Government in 1979³
- Three overarching principles:
 - 1 Respect for persons
 - 2 Beneficence
 - 3 Justice
- Three policy implications:
 - Informed consent
 - Assessment of risks/benefits
 - Care for vulnerable populations

³<http://www.hhs.gov/ohrp/humansubjects/guidance/belmont.html>

Benefits and Harm

- What is a “benefit”?
- What is a “harm”?
- How do we balance the two?

Ethical Considerations

- Most ethical issues are not unique to *experimental social science*
- Some especially important issues:
 - 1 Randomization
 - 2 Informed consent
 - 3 Privacy
 - 4 Deception
 - 5 Publication bias

I. Randomization

- Is it ethical to randomize?

II. Informed Consent

- Persons must consent to being a research subject

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- What this means in practice is complicated
 - What is consent?
 - What is “informed” consent?
 - What exactly do they have to consent to?

II. Informed Consent

- Persons must consent to being a research subject
- What this means in practice is complicated
 - What is consent?
 - What is “informed” consent?
 - What exactly do they have to consent to?
- Cross-national variations
 - Consent forms required in U.S.
 - Not required in UK

III. Privacy

- Under EU Data Protection Directive (1995), data can be processed when:
 - Consent is given
 - Data are used for a “legitimate” purpose
 - Anonymous or confidential
- These rules have become more expansive under GDPR (in force as of 2018)
- Data cannot leave the EU except under conditions

III. Privacy

- Experimental might be additionally sensitive

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- Experimental might be additionally sensitive
- Answers reflect “manipulated” attitudes, behaviors, perceptions, etc. that respondents may not have given in another setting

IV. Deception

- Major distinction between psychology tradition and economics tradition⁴
 - Purpose of the study
 - Purpose of specific items or tasks
 - Order or length of questionnaire

⁴Dickson, E. 2011. "Economics versus Psychology Experiments." *Cambridge Handbook of Experimental Political Science*.

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 - Omission: In a multi-round trust game, an additional round is added
 - Commission: Telling respondents it is a dictator game, but it is actually a trust game

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V. Publication Bias

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- If studies are meant to policy or practical implications, then we care about PATE or a set of CATEs, including whether their effects are positive, negative, or zero.

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- If studies are meant to policy or practical implications, then we care about PATE or a set of CATEs, including whether their effects are positive, negative, or zero.
- Publication bias (toward “significant” results) invites wasting resources on treatments that actually don’t work

Lots of Other Ethical Questions

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1 Funding

Lots of Other Ethical Questions

- 1 Funding
- 2 Independence and Politicization

Lots of Other Ethical Questions

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- 1 Explain how to analyze experiments quantitatively.
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- 3 Evaluate the uses and limitations of several common survey experimental paradigms.
- 4 Identify practical issues that arise in the implementation of experiments and evaluate how to anticipate and respond to them.

Wrap-up

- Thanks to all of you!
- Stay in touch (t.leeper@lse.ac.uk)
- Good luck with your research!

5 Beyond One-Shot Designs

6 Behavioral Outcomes

Beyond One-shot Designs

- Surveys can be used as a measurement instrument for a field treatment or a manipulation applied in a different survey panel wave
 - 1 Measure effect duration in two-wave panel
 - 2 Solicit pre-treatment outcome measures in a two-wave panel
 - 3 Measure effects of field treatment in post-test only design
 - 4 Randomly encourage field treatment in pre-test and measure effects in post-test

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 - 3 Measure effects of field treatment in post-test only design
 - 4 Randomly encourage field treatment in pre-test and measure effects in post-test
- Problems? Compliance & nonresponse

I. Effect Duration

- Use a two- (or more-) wave panel to measure duration of effects
 - T1: Treatment and outcome measurement
 - T2+: Outcome measurement
- Two main concerns
 - Attrition
 - Panel conditioning

II. Within-Subjects Designs

- Estimate treatment effects as a difference-in-differences
- Instead of using the post-treatment mean-difference in Y to estimate the causal effect, use the difference in pre-post differences for the two groups:

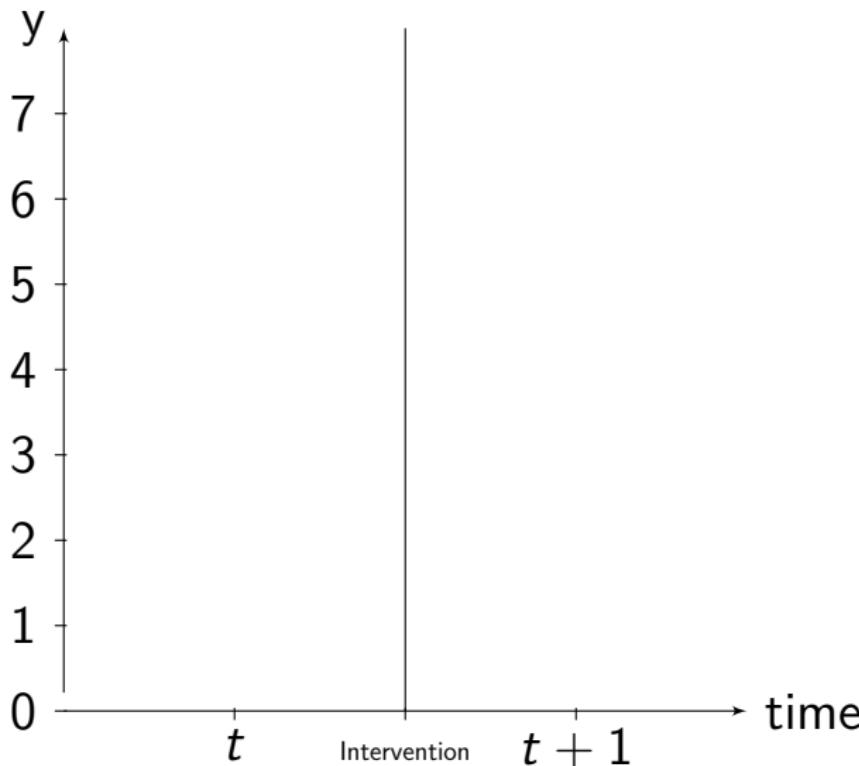
$$(\hat{Y}_{0,t+1} - \hat{Y}_{0,t}) - (\hat{Y}_{j,t+1} - \hat{Y}_{j,t})$$

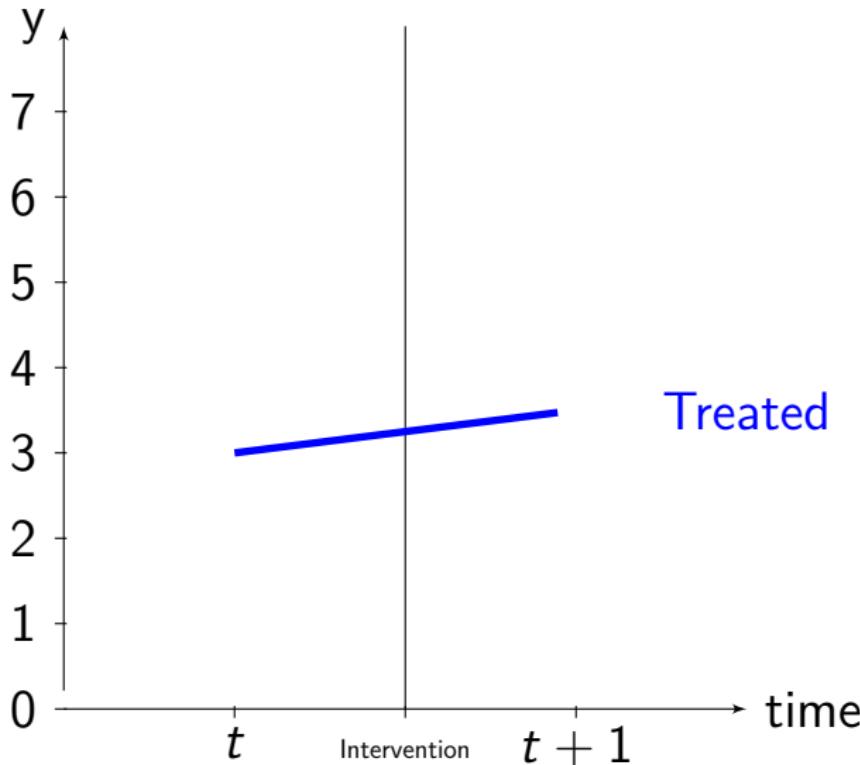
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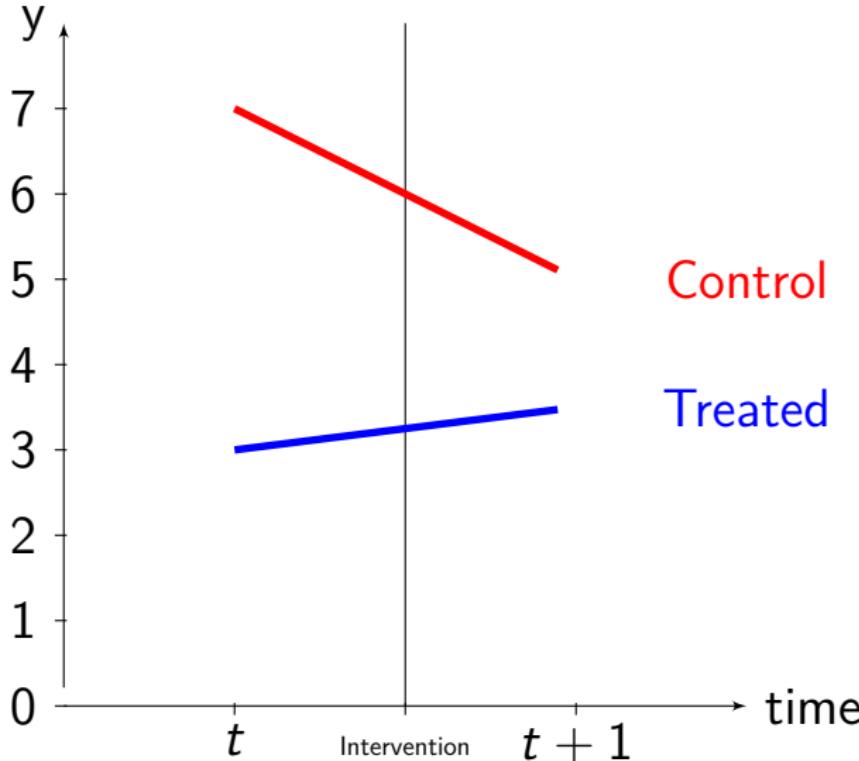
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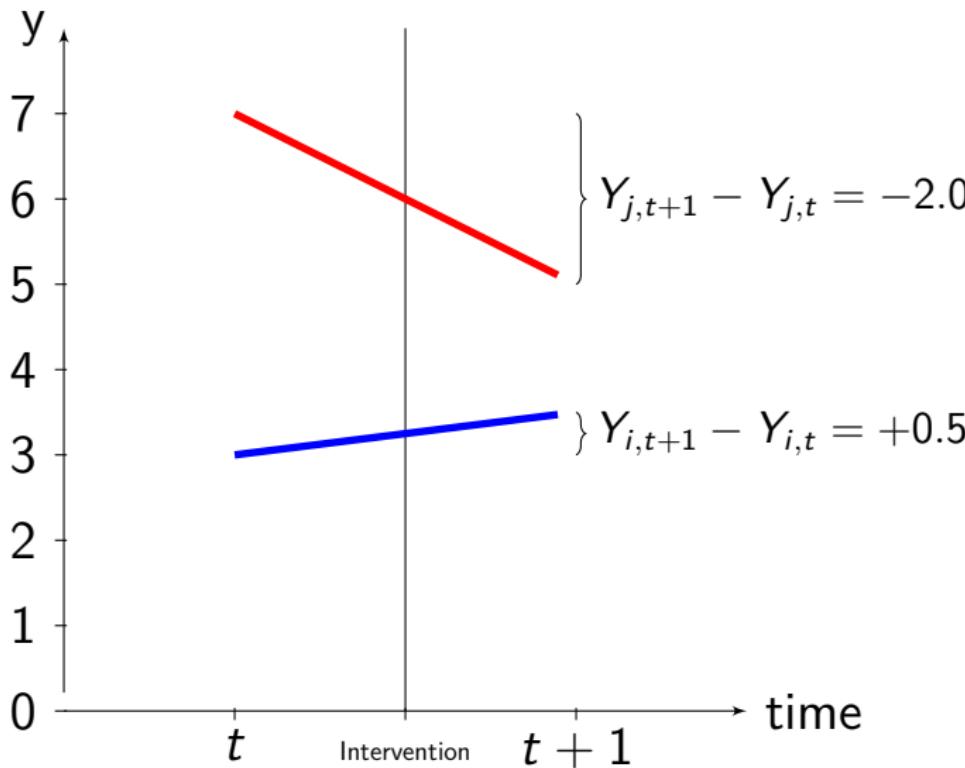
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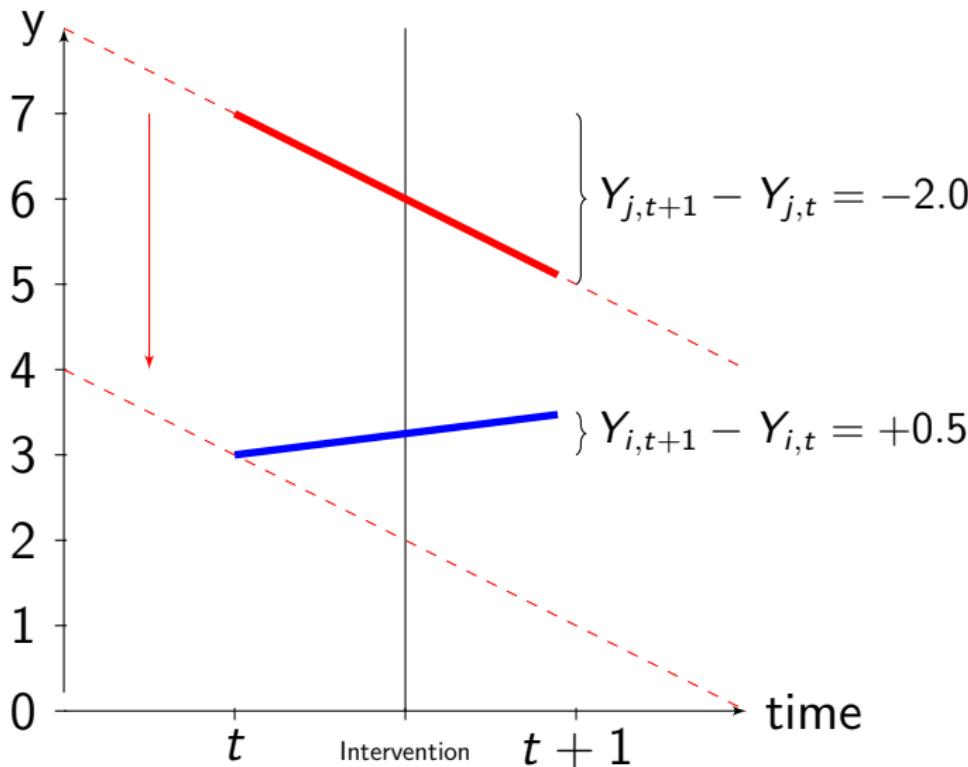
- Advantageous because variance for paired samples decreases as correlation between t_0 and t_1 observations increases

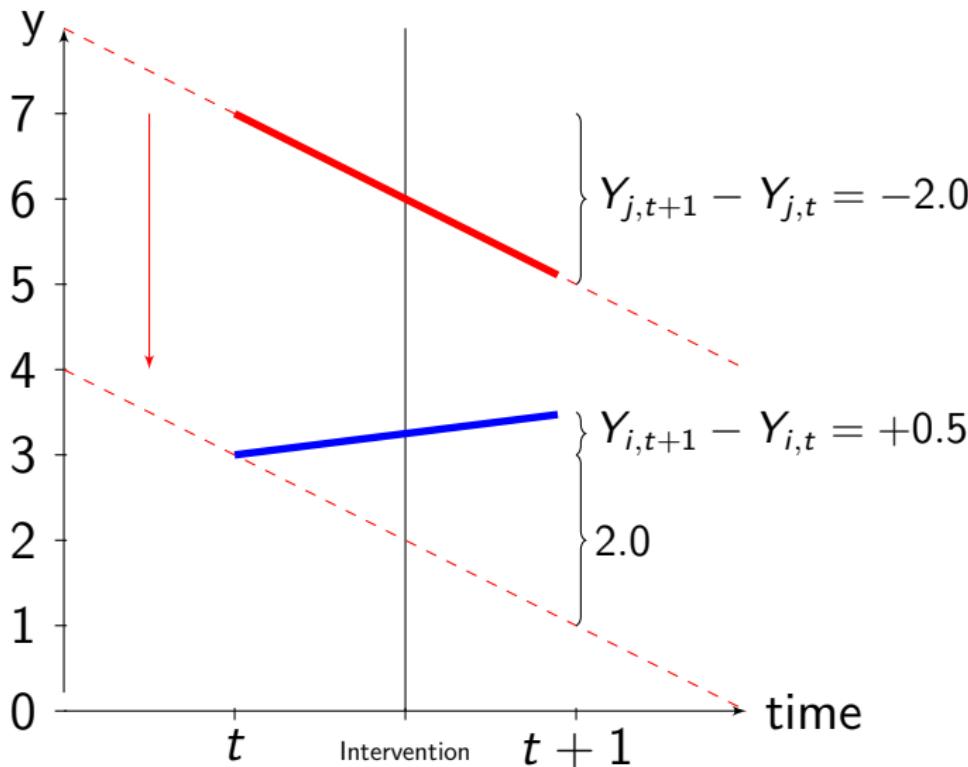


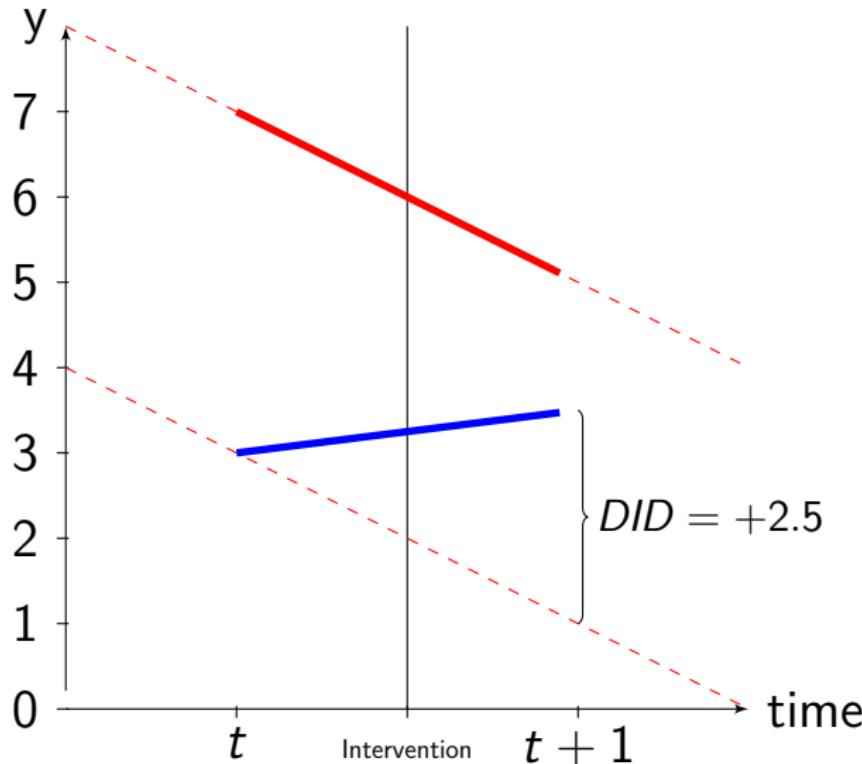












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As soon as time comes into play, we have to worry about threats to validity.⁵

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III. Randomized Field Treatment

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- Issues
 - Nonresponse
 - Noncompliance

Noncompliance

- Compliance is when individuals receive and accept the treatment to which they are assigned
- Noncompliance:
“when subjects who were assigned to receive the treatment go untreated or when subjects assigned to the control group are treated”⁶
- This causes problems for our analysis because factors other than randomization explain why individuals receive their treatment
- Lots of methods for dealing with this, but the consequence is generally reduced power

⁶Gerber & Green. 2012. *Field Experiments*, p.132.

Asymmetric Noncompliance

- Noncompliance *asymmetric* if only in one group
- We can ignore non-compliance and analyze the “intention to treat” effect, which will underestimate our effects because some people were not treated as assigned

$$ITT = \bar{Y}_1 - \bar{Y}_0$$

- We can use “instrumental variables” to estimate the “local average treatment effect” (LATE) for those that complied with treatment:

$$LATE = \frac{ITT}{PercentCompliant}$$

- We can ignore randomization and analyze data “as-treated”, but this makes our study no longer an experiment

Local Average Treatment Effect

- IV estimate is *local* to the variation in X that is due to variation in D
- LATE is effect for those who *comply*
- Four subpopulations:
 - Compliers: $X = 1$ only if $D = 1$
 - Always-takers: $X = 1$ regardless of D
 - Never-takers: $X = 0$ regardless of D
 - Defiers: $X = 1$ only if $D = 0$
- Exclusion restriction! Monotonicity!

Two-Sided Noncompliance

- Two-sided noncompliance is more complex analytically
- Stronger assumptions are required to analyze it and we won't discuss them here
- Best to try to develop a better design to avoid this rather than try to deal with the complexities of analyzing a broken design

IV. Treatment Encouragement

- Design:
 - T1: Encourage treatment
 - T2: Measure effects
- Examples:
 - 1 Albertson and Lawrence⁷

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Treatment Noncompliance

Treatment Noncompliance

- Several strategies
 - “As treated” analysis
 - “Intention to treat” analysis
 - Estimate a LATE

Questions?

Heterogeneity due to *Outcomes*

- This is expected!
 - E.g., non-equivalent outcomes
- Reasonable to explore multiple outcomes
 - Multiple comparisons
 - Power considerations
 - Construct validity

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- This is expected!
 - E.g., non-equivalent outcomes
- Reasonable to explore multiple outcomes
 - Multiple comparisons
 - Power considerations
 - Construct validity
- What outcomes you measure depend on your theory
- Lots of potential for behavioral measures!

Behavioural measures

Some behaviours that can be directly measured through survey questionnaires.

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Three broad categories:

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- 1 Behavioural measures that provide survey paradata

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- 3 Behavioural measures that operationalize behaviours

Behavioural Measures for Paradata

Why?

- Respondents use of the survey tells us something meaningful about their behaviour

Behavioural Measures for Paradata

Why?

- Respondents use of the survey tells us something meaningful about their behaviour

What?

Behavioural Measures for Paradata

Why?

- Respondents use of the survey tells us something meaningful about their behaviour

What?

- Nonresponse

Behavioural Measures for Paradata

Why?

- Respondents use of the survey tells us something meaningful about their behaviour

What?

- Nonresponse
- Response latencies

Behavioural Measures for Paradata

Why?

- Respondents use of the survey tells us something meaningful about their behaviour

What?

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- Reading times

Behavioural Measures for Paradata

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Behavioural Measures for Paradata

Why?

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What?

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- Eye tracking

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- Respondents use of the survey tells us something meaningful about their behaviour

What?

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- Eye tracking
- Mouse tracking
- Smartphone metadata

Behavioural Measures for Attitudes

Why?

- Attitudinal self-reports might be “cheap talk”

Behavioural Measures for Attitudes

Why?

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What?

Behavioural Measures for Attitudes

Why?

- Attitudinal self-reports might be “cheap talk”

What?

- Implicit Association Test

Behavioural Measures for Attitudes

Why?

- Attitudinal self-reports might be “cheap talk”

What?

- Implicit Association Test
- Incentivized Survey questions

Behavioural Measures for Behaviour

Why?

- We want to observe or affect behaviour (e.g., in an experiment)

Behavioural Measures for Behaviour

Why?

- We want to observe or affect behaviour (e.g., in an experiment)

What?

- Directly measure or initiate a direct measure of a behaviour
- May be measured by something that occurs within the confines of the survey or something outside of the survey

Example 1: Active Information Choice

⁸Guess, AM. 2015. "Measure for Measure." *Political Analysis* 23: 59–75. doi:10.1093/pan/mpu010

⁹Leeper, TJ. 2014. "The Informational Basis for Mass Polarization." *Public Opinion Quarterly* 78(1): 27–46. doi:10.1093/poq/nft045

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Reports From the Hive,
Where the Swarm
Concurs

Pay for Performance
Improves Quality of
Health Care Through
Collaborative Medicine

Why are 3-D Movies so
Bad?

Physicians Group Says
Quality Will Improve
Under Outcome-based
Payments

Council Is Set to
Consider Increases in
Hotel and Property Taxes

Doctors Can Work
Together to Improve
Patient Health, But Need
Appropriate Incentives

Patients Better Served
When Providers Paid for
Health Outcomes

Improving America's
Health Requires Provider
Incentives, Not 'Fee-for-
Service'

When Paid for Outcomes,
Doctors Have Little
Reason to Treat Highest
Risk Patients

A Bowl of Chili with
Bragging Rights

SEC Vote Requires
Business Filings to Add
Environmental Risks to
Bottom Line

Anatomy of a Tear-
Jerker

Spammers Use the
Human Touch to Avoid
CAPTCHA

USDA Raises Corn
Export Outlook

Will a Standardized
System for Verifying
Web Identity Ever
Catch On?

Wellness, Rather
Than Illness, Is Focus
Under Outcome-
Accountable Care

Gender Differences in
Education Need
Innovative Solution

Heart Attack While
Dining at Heart Attack
Grill in Las Vegas

Out of the O.R., T.R.
Knight Back Onto the
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Paying Doctors Based
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Stage: Primary Election

Sub-stage: Early Primary

Time Remaining: 21:26

6:46

Andy Fischer's Political Experience

DELEGATE COUNT, END OF FEBRUARY

Republican Primary

Sam Green's Mother provides a Childhood Anecdote

Dana Turner's Picture

Terry Davis's Current Job Performance

Taylor Harris's Age

Iowa General Election

January, 2008

Time remaining: 5:23

Hillary Clinton wins in South Dakota!



◀ ▶ 5:23 / 5:23

Stage: Pre-Election

Sub-stage: PE-2

Time Remaining: 0:00

0:00

Question 1 of 1

Primary elections require voters to choose the party they want to vote in. Before we begin the Iowa primary, please choose either the the Republican or Democrat Primary. You will see candidates for both parties but will be only able to vote in the party you choose.

- Republican
- Democrat

Select an answer, then click the End button to end the questionnaire.

End

Example 2: Sign-up/Enrolment

An extension of information choice behaviour would be explicit engagement in other kinds of (small) behaviours, such as:

- Entering an email address to receive information or join a mailing list^{12 13}
- Signing up for an appointment or further interaction

¹²Leeper, T.J. 2017. "How Does Treatment Self-Selection Affect Inferences About Political Communication?" *Journal of Experimental Political Science*: In press.

¹³Bolsen, Druckman, & Cook. 2014. "Communication and Collective Actions." *Journal of Experimental Political Science* 1(1): 24–38. doi:10.1017/xps.2014.2

Example 3: Incentivised Survey Questions

Definitions:

- A survey question is just a self-report
- An *incentivized* survey question attached financial gains or losses to the answer options

Mark your gamble selection with an X in the last column across from your preferred gamble.

Gamble	Event	Payoff	Probabilities	Your Selection
1	A	\$10	50%	
	B	\$10	50%	
2	A	\$18	50%	
	B	\$6	50%	
3	A	\$26	50%	
	B	\$2	50%	
4	A	\$34	50%	
	B	-\$2	50%	
5	A	\$42	50%	
	B	-\$6	50%	

Eckel & Grossman. 2008 "Forecasting risk attitudes." *Journal of Economic Behavior & Organization* 68(1): 1-17.
doi:10.1016/j.jebo.2008.04.006

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Paradigm could be applied to any measure of behavioural intentions to avoid cheap talk.

Example 4: Purchasing Decisions

Common ways to study purchasing behaviour include:

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Another way is embedding a purchase in a survey.¹⁴

¹⁴Bolsen, T. 2011. "A Lightbulb Goes On." *Political Behavior* 35(1): 1–20. 10.1007/s11109-011-9186-5



Example 5: Donations

- Miller and Krosnick¹⁵ asked for charitable donations via cheque directly as part of a paper-and-pencil survey

¹⁵Miller, Krosnick, & Lowe. N.d. "The Impact of Policy Change Threat on Financial Contributions to Interest Groups." Working paper.

¹⁶Klar & Piston. 2015. "The influence of competing organisational appeals on individual donations." *Journal of Public Policy* 35(2): 171–91. doi:10.1017/S0143814X15000203

Example 5: Donations

- Miller and Krosnick¹⁵ asked for charitable donations via cheque directly as part of a paper-and-pencil survey
- Klar and Piston¹⁶ offered respondents a survey incentive up-front for participation and then later offered them a chance to donate (a portion of payment) to a charity

¹⁵Miller, Krosnick, & Lowe. N.d. "The Impact of Policy Change Threat on Financial Contributions to Interest Groups." Working paper.

¹⁶Klar & Piston. 2015. "The influence of competing organisational appeals on individual donations." *Journal of Public Policy* 35(2): 171–91. doi:10.1017/S0143814X15000203

Example 6: Web Tracking Data

- 1 Active installation of a tracking app, such as YouGov Pulse¹⁷ ¹⁸
- 2 Post-hoc collection of web history files using something like Web Historian ¹⁹

¹⁷ <https://yougov.co.uk/find-solutions/profiles/pulse/>

¹⁸ Guess, AM. N.d. "Media Choice and Moderation." Working paper, <https://dl.dropboxusercontent.com/u/663930/GuessJMP.pdf>.

¹⁹ <http://www.webhistorian.org/>

Other Possibilities

²⁰Mao, Mason, Suri, Watts. 2016. "An Experimental Study of Team Size and Performance on a Complex Task." *PLoS ONE* 11(4): e0153048. doi:10.1371/journal.pone.0153048

Other Possibilities

- Coordination tasks
 - Synchronous group tasks²⁰
 - Game play
 - Simulations

²⁰Mao, Mason, Suri, Watts. 2016. "An Experimental Study of Team Size and Performance on a Complex Task." *PLoS ONE* 11(4): e0153048. doi:10.1371/journal.pone.0153048

Event Records Map Documents Notifications Help **Typhoon Pabuk** **drakes** **McDonalds** **Intergo** **superbrands** **supermarts**

RSS **#Pabuk #Davao #74 #muertos den** **#igpapu**

RSS **#lo ang pinaka nakuatakaw ni nangyan ito sa CDO katapun #PabukPH**

RSS **#gclima** **Jacon via #japonica** El centro del #TYP_n #Bipha a 180km al Este de Pto. Princess Panawan Filipinas. Vertes 160kph [http://bit.ly/codkaycon](http://bit.ly/...</p>
<p>RSS Magnitude 6.0 Villages submerged <a href=)

RSS **Damages in Davao Mall** **Damages after** **#TyphoonOMA** <http://bit.ly/codkaycon>

RSS **NDRRMC explains disparity** **between its death count vs. numbers from the ground** <http://bit.ly/codkaycon>

RSS **PHOTO: Uprooted tree at Rizal Blvd.** **Davao City after #PabukPH** | via **YouScopeer @keymarddy** <http://bit.ly/CDPFWYD3>

RSS **Dahil sa Typhoon #PabukPH. <** **@gmanews ditto po sa Cagayan Cdo O** **9000** <http://bit.ly/HTEVHgQ>

Chat Rooms **New Room** In room **mapping chat**

mapping chat

AndyZLL: **inted212** I know, some say damage to an area though along with were it was

Mapping chat: **inted212** To know what the storm is doing Magna2d2: sort this post and pre cross

maked212: That would be relevant then **AndyZLL** **cerat15** the storm is over, so all the tweets that give storm location without being any damages are irrelevant

Magna2d2: if the storm has passed or hasn't is relevant

maked212: All your comments for the requesters after octogen2d2

Magna2d2: I think its good to track the storm and locate damage that has already happened, not track movement of storm

cerat15: perhaps, but our task is to only classify and locate damage that has already happened, not track movement of storm

Magna2d2: I think we have to many empty events with nothing happening on the page

Celto: lol yeah, can't agree since people are editing locations and regions we have more classifiers for specific events and regions etc? This is quite confusing

Magna2d2: We are still getting organized

AndyZLL: Lots of things to sift through, just takes time

GTAS15: as we delete or make events for more of the tweets, the more organizers will get, we can always combine events later. I think it is most important to sort through tweets

cerat15: lol

McDonalds: All I've been doing is sorting through tweets to try and clean it up a bit. Hopefully I'll make it easier in the end

Celto: so delete all tweets tracking storm? I can get on that lol if needed

123.14, 9.64

Other Possibilities

- Coordination tasks
 - Synchronous group tasks²⁰
 - Game play
 - Simulations

²⁰Mao, Mason, Suri, Watts. 2016. "An Experimental Study of Team Size and Performance on a Complex Task." *PLoS ONE* 11(4): e0153048. doi:10.1371/journal.pone.0153048

Other Possibilities

- Coordination tasks
 - Synchronous group tasks²⁰
 - Game play
 - Simulations
- Offering incentives to perform future behaviour
(tracked elsewhere)

²⁰Mao, Mason, Suri, Watts. 2016. "An Experimental Study of Team Size and Performance on a Complex Task." *PLoS ONE* 11(4): e0153048. doi:10.1371/journal.pone.0153048

Other Possibilities

- Coordination tasks
 - Synchronous group tasks²⁰
 - Game play
 - Simulations
- Offering incentives to perform future behaviour (tracked elsewhere)
- OAuth/API integrations w/ other platforms
 - Merging website usage data w/ survey data
 - Treating website sign-up or usage as behavioural outcomes
 - Linking with smartphone metadata

²⁰Mao, Mason, Suri, Watts. 2016. "An Experimental Study of Team Size and Performance on a Complex Task." *PLoS ONE* 11(4): e0153048. doi:10.1371/journal.pone.0153048

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- 4 Validate, validate, validate!

Activity!

With a partner, brainstorm how one or more these behavioural measures might be applied to a survey experiment (either as outcome, treatment, covariate, or behavioural check) relevant to your own work or your organisation.