Digital Experimentation Methods

Session 9: Observational Causal Studies

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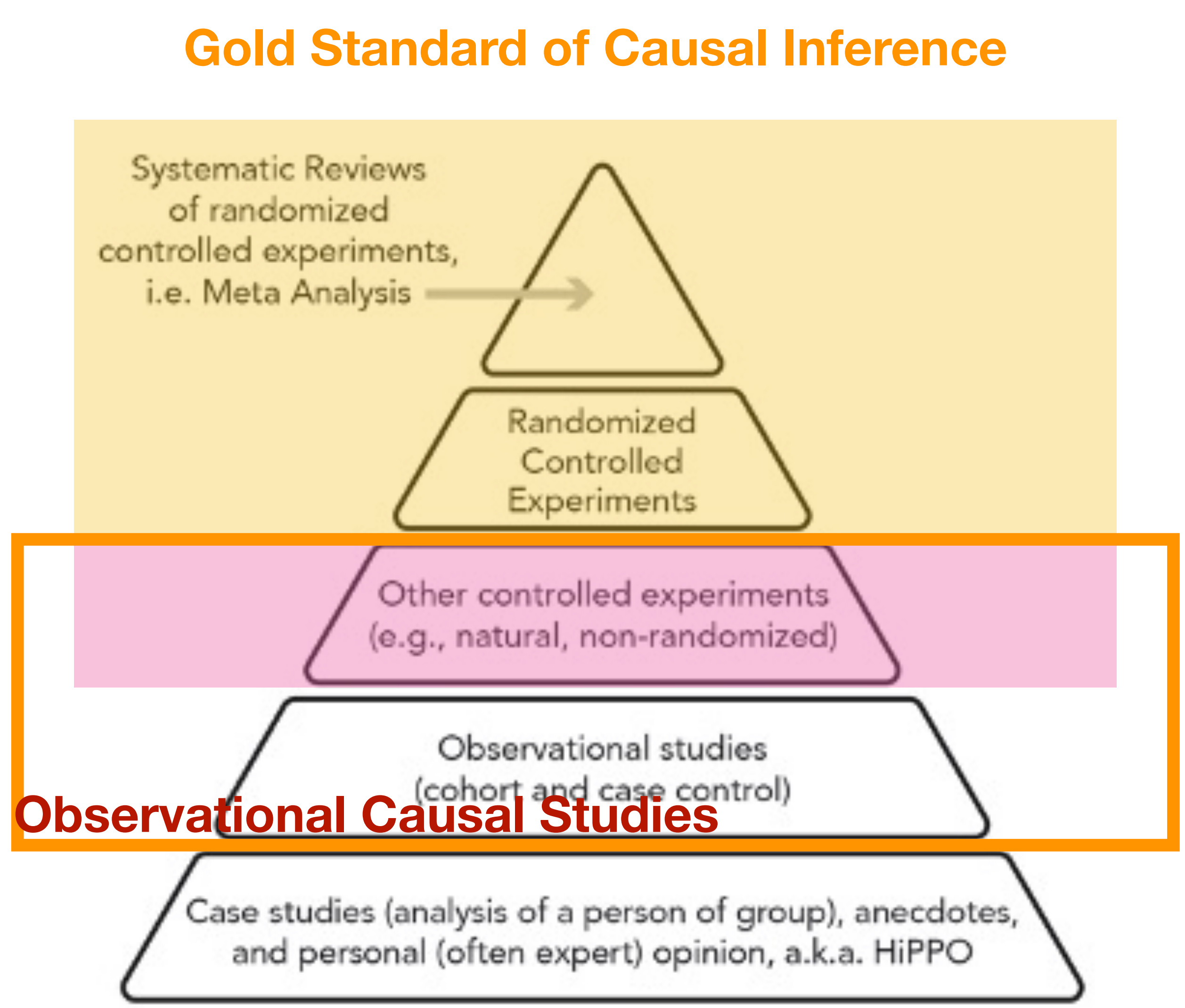
Hierarchy of Evidence

- Random Assignments of Variants (Treatments)
  - Randomized Controlled Experiments
  - Multiple randomized controlled experiments
    - Fisher's Meta-Analysis
- As you go down, the trust level declines
- Other Controlled Experiment : Treatment without Random Assignment
- Observational Studies: No Treatment
- Case Studies: Subjective Evidence



Observational Causal Studies

- More complex in data analysis with low trust in causal effects.
- Harder to scale it up in companies, compared to A/B testing.
- Companies started to invest in observational causal studies about 3 (China) -5(US) years ago.
- Randomized controlled experiments started about 5 (China) - 10 (US) years ago.
- Data-driven (informed) decision makings are the future.
- Only causal effects can inform the choices among different strategies.

When Controlled Experiments Are Not Possible

A. What are the treatment and control groups?

B. Is there a random assignment of the treatment? Why?

- What is the impact on product engagement if a user switches their phone from an iPhone to an Android?
- What is the impact of Apple's policy change on WeChat user behaviors?
- What is the impact of Tiktok's new features on Kuaishou's users' behaviors?
- What is the impact of COVID-19 on users' social behavior on Facebook/WeChat?

When Controlled Experiments Are Not Possible

- When the change to be tested is not under the control of organizations.
  - Third party's decision
  - Competitors' decision
  - Users' decisions
  - Natural disasters
- When establishing a *Control* may incur too large an opportunity cost
  - Experiments can be costly during the rare event
    - A new feature for red pockets during the spring festival
    - Running ads during Super Bowl
    - Measure the long-term treatment effects
- When true randomization is hard
  - Network interferences, SUTVA

Quasi-experiments

- The goal is to measure the causal impact of a change (treatment).
- Compare the outcome of a treated population (treatment) to the outcome for an untreated population (control).

Outcome for treated - Outcome for untreated

= [Outcome for treated - Outcome for treated if not treated] +
[Outcome for treated if not treated - Outcome for untreated]

= Treatment Effects on treated + Selection bias

To minimize it. It's almost impossible to completely remove it without randomization

Quasi-experiments

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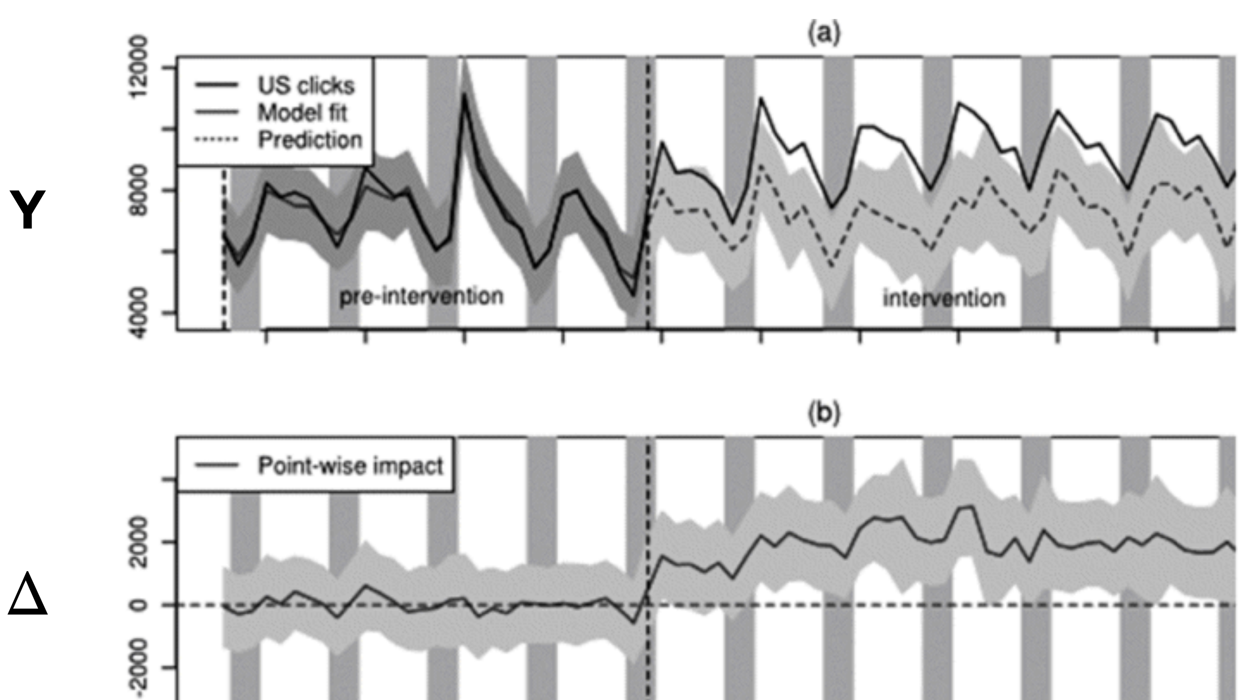
Minimize the difference between Control and Treatment

- Challenges are:
  - How to construct Control and Treatment Groups
  - How to model the impact given those Control and Treatment Groups

Interrupted Time Series (ITS)

- A Quasi-Experiment Design: Treatment without a TRUE randomization
- Use the same population for Control and Treatment
- Vary what the population experiences over time.
    - e.g., treatment is a big shock to products and cannot be controlled



[Bayesian structural time series]

1. **Use the data before the Treatment to train the model for prediction.**
2. **- - Counterfactual Y after launching the new feature: Model Predictions**

Interrupted Time Series (ITS)

- The prediction model considers only the information before the treatment
- Confounding Factors
    - The factor unique to post-treatment periods
        - Time effects
        - new changes after launching new features
- How could we improve the design?
    - Switch on & off of the treatment multiple times
        - Average out the confounding effects
    - What are the risks?
        - Hurt user experience

Regression Discontinuity Design (RDD)

- A methodology to identify the Comparable Treatment and Control Groups by a clear threshold.
- Treatment: Just above the threshold
- Control: Just below the threshold
- Example: Study the effects of university education on Income
  - University admission line is 570
  - Treatment: Just above 570 e.g., [570,575]
  - Control: Just below [565,570)
  - Among the people [565,575], passing the line is likely a random assignment.

Almost the Same expect for taking university

Regression Discontinuity Design

- Goal: Assess the impact of drinking on deaths
- Facts: Americans over 21 can drink legally
- What is the RDD design to answer this question? (Threshold)
  - Threshold: 21 years old
  - Compare the death rate among those just below and above 21 years old.
- What can be the confounders?
  - Other factors that share the same threshold
  - e.g., the legal age of 21 is also for legal gambling

Regression Discontinuity Design

- Carpenter, Christopher, and Carlos Dobkin. "The effect of alcohol consumption on mortality: regression discontinuity evidence from the minimum drinking age." *American Economic Journal: Applied Economics* 1, no. 1 (2009): 164-82.

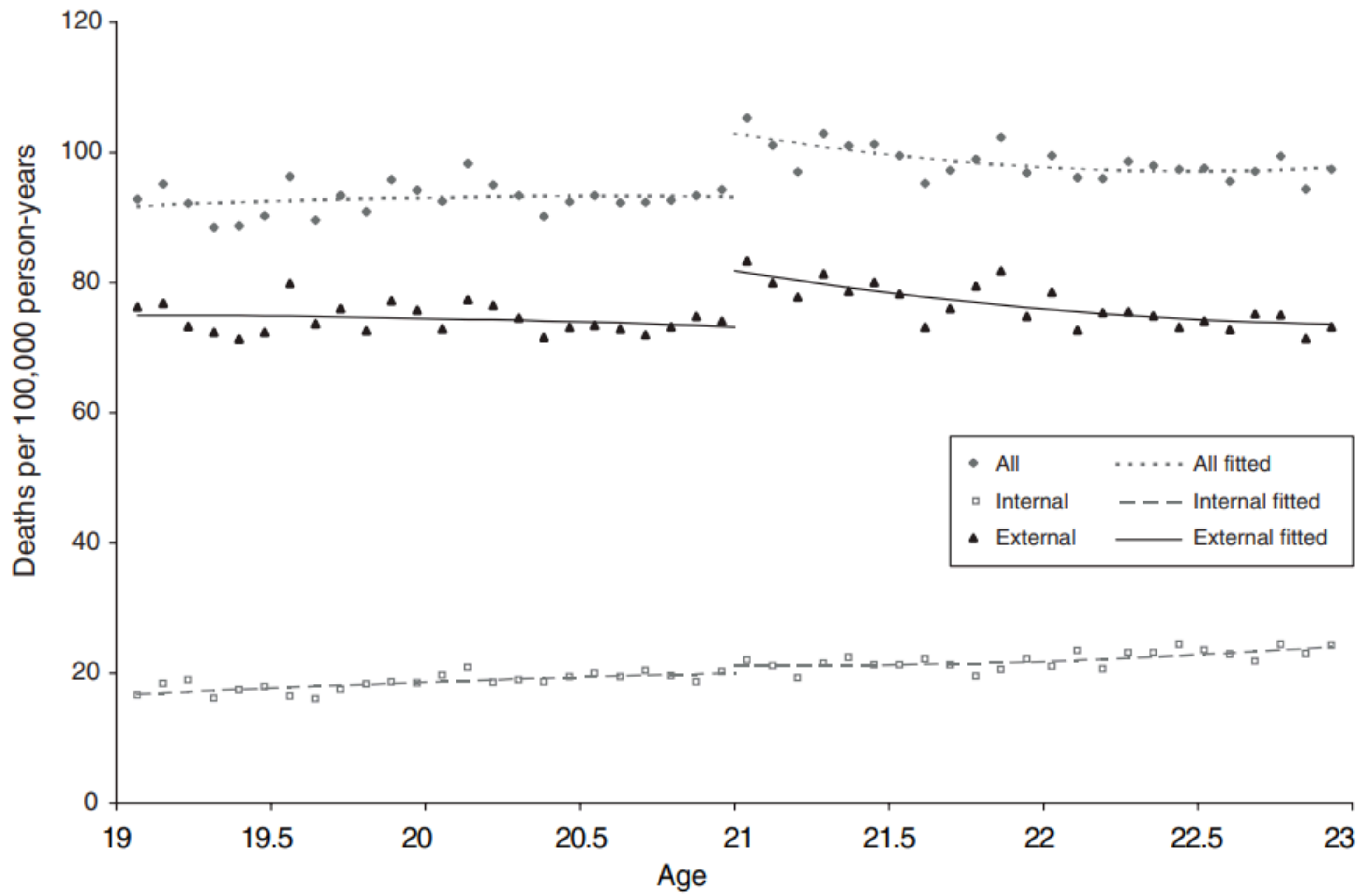


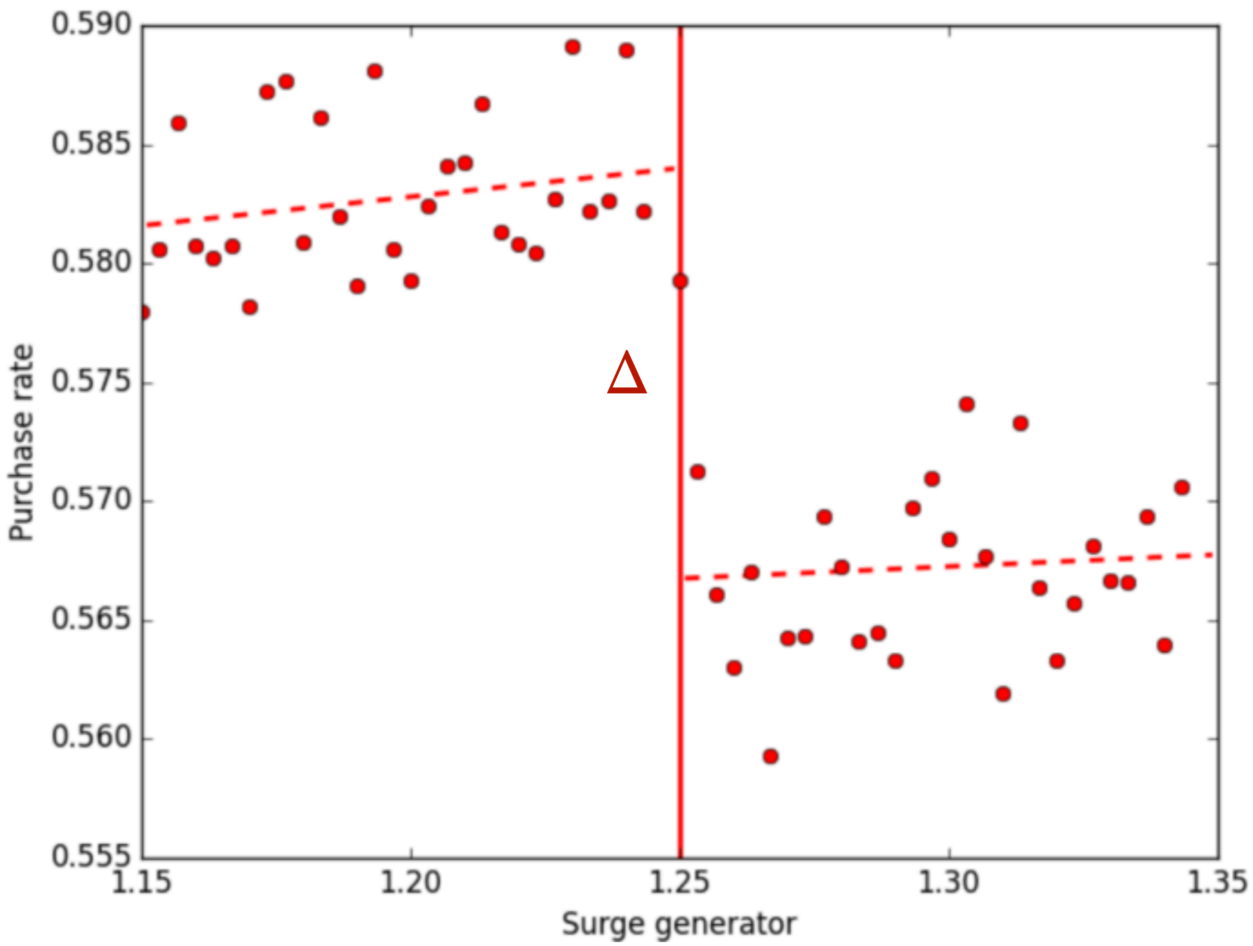
FIGURE 3. AGE PROFILE FOR DEATH RATES

Notes: Deaths from the National Vital Statistics Records. Includes all deaths that occurred in the United States between 1997–2003. The population denominators are derived from the census. See online Appendix C for a list of causes of death.

Regression Discontinuity Design @ Uber

Effects of Surge Pricing on Demand of Uber (purchase rate)

- Sharp Cutoff: surge generator = 1.25
- Assumption: very close to the cut-off point are similar with respect to any relevant confounding variables.
- What is the RDD design?
  - Treatment: Just Above 1.25 and with surge price
  - Control: Just Below 1.25 and without surge price



Regression Discontinuity Design

- A sharp cutoff, e.g.,
  - eBay sellers' score > T can get a badge.
    - Identify the signaling effects of badge on sales
  - Taobao sellers' sales > T are provided with a new tool
    - Identify the effects of new tool on sales
- Assumptions:
  - Users just above and below the cutoff are of no differences on Y except for receiving the treatment or not.
  - "Almost Random" Assignment is based on the cutoff

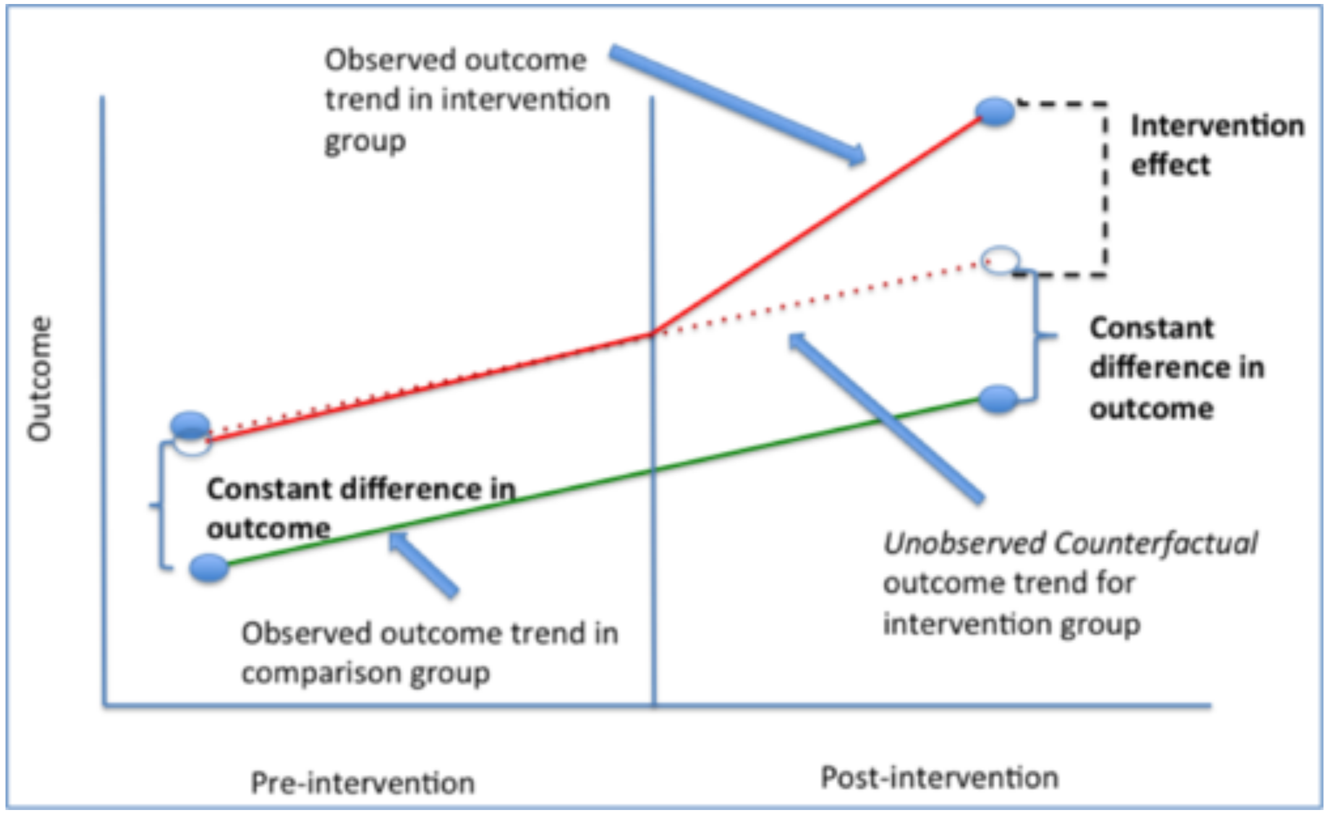
Difference-in-Difference

1. A policy only impacts a subset of users

- e.g., a new feature is first launched on iPhone users
    - However, iPhone users are systematically different from Android users.
    - Find a group of Android users as Control
        - **Check whether the trends on Y (metrics) before the Treatment are the same or not for the users.**

Identify the Control Group

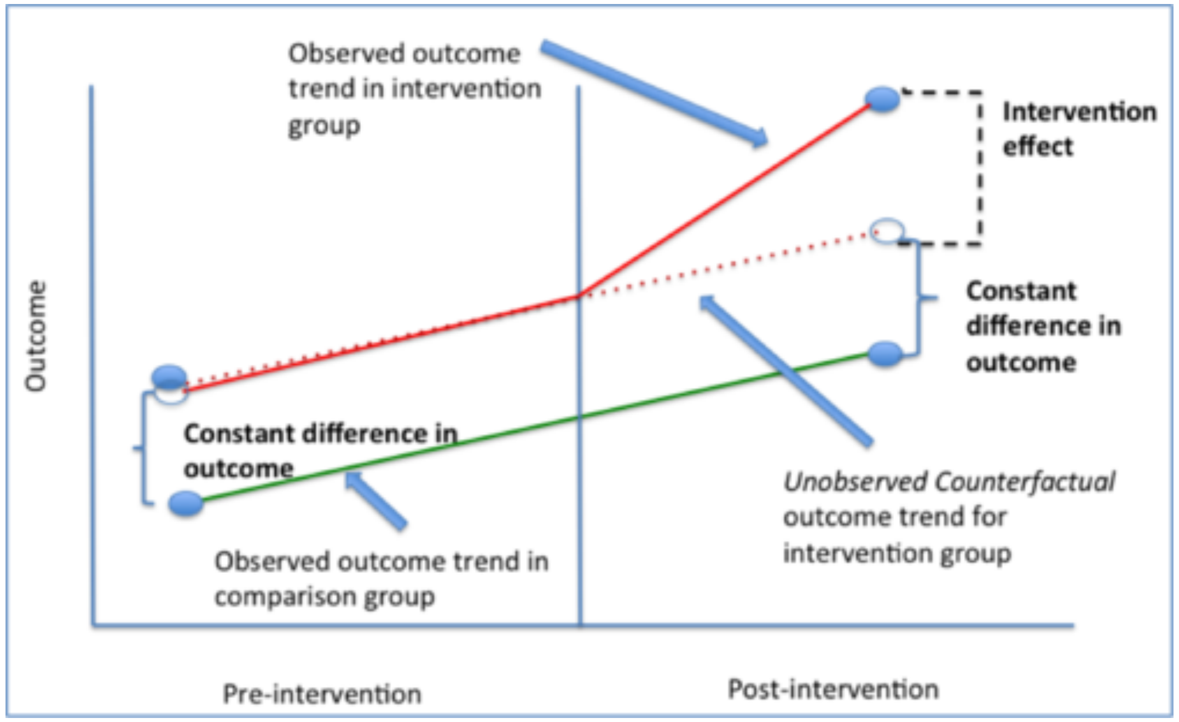
- Use the control group to control for the confounding effects
- Assume the same trends without the treatment after the treatment



DiD Procedure

1. A quasi-experimental design
2. Utilize longitudinal data from treatment and control groups to obtain an appropriate counterfactual (control group) to estimate a causal effect.
    - The Control group trend on Y is the counterfactual for the Treatment group trend on Y if not treated.
    - Without the Treatment, two groups should have the same trends on Y.
    - Treatment changes the trend for the Treatment Group
3. Compare Treatment and Control groups - Treatment Effects
    - $Y_i = \alpha + \beta_1 T_i + \beta_2 D_i + \gamma D_i T_i + \epsilon_i$
    - Ti: dummy (after launching the Treatment)
    - Di: dummy (receive the Treatment)
    - γ : Treatment Effects (whether the Treatment significantly changes the trend)

Which parameter captures the treatment effects?



Example: DiD @ Seeking Alpha

Chen, Hailiang, Yu Jeffrey Hu, and Shan Huang. "Monetary incentive and stock opinions on social media." *Journal of Management Information Systems* 36.2 (2019): 391-417.

- Seeking Alpha is one of the biggest investment-related social media websites in the U.S.
- In January 2011, SA launched a premium partnership program that enables its contributors to earn $10 per 1,000 page views received by their "premium" articles
    - What is the treatment here?
    - Monetary Incentive for content contribution
- We used DID approach to examine the impact of this policy change.

Example: DiD @ Seeking Alpha

- Treatment: Users who participated in the program
- Control: Users who did not participate in the program
- Assumptions:
  - Control Group's users were not affected by the policy change
  - Control Group's trend on Y is very similar to that of Treatment Group before the policy change

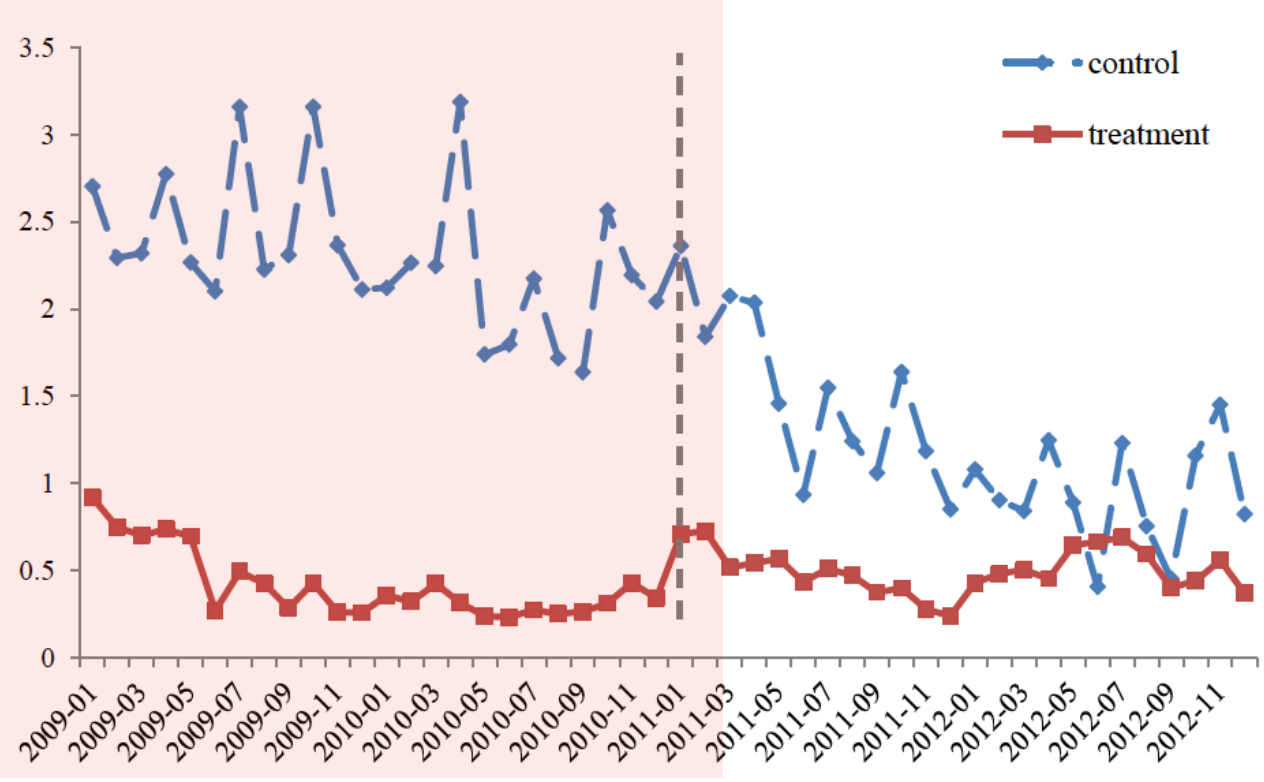


Figure 1. Average number of articles per contributor in each month

Propensity Score Matching

- Construct two comparable groups of units based on observed characteristics.
- Comparable in the sense that:
  - They share the variables that can impact the metrics
  - e.g., OEC is user engagement (# visits /week)
    - Control and Treatment Groups are (almost) the same on the variables that can affect engagement
- Propensity Score Matching (PSM) provides a way to construct two comparable groups.

Propensity Score Matching

- Instead of matching on covariates directly, PSM matches on a single number: the propensity score
  - $p_i = pr(T_i | X_i) = \dfrac{exp[\beta_0 + \beta_1 X + \epsilon_i]}{1 + exp[\beta_0 + \beta_1 X + \epsilon_i]}$
  - $|p_i - p_j| < \sigma$ (a small number)
- (i, j) are (almost) equally likely to be treated but happen to be in control and treatment groups.
  - Users i and j are equally likely to adopt a new feature.
  - User i happens to adopt it, while user j happens not to.
- Find many such pairs and construct Control (j) and Treatment (i) Groups.

Propensity Score Matching

- A useful methodology to construct comparable/matched groups: Treated units vs. Untreated units
  - Android vs. iPhone users
  - Comparable cities
- PSM is one of the most popular matching methods used in the industry.
- Other popular matching methods:
  - Synthetic Control
  - Coarsened Exact Matching (CEM)
- Can we combine PSM and DiD? How?
  - Use PSM to construct the groups with similar trends before the treatment

Wrap-up

1. A/B testing Terminology and Overview
2. Statistics behind A/B testing
    1. Statistical tests (t, z, chi-square)
    2. Confidence intervals
    3. Type I error & Multiple Testing
    4. Type II error & Power Analysis
    5. Regression
3. Internal & External Validity
    1. Sanity Checks (SRM, Randomization checks, A/A tests)
    2. SUTVA (network interferences)
    3. Survivorship bias
    4. Heterogeneous Treatment Effects
    5. Novelty and Primacy Effects
4. Improve Sensitivity
    1. Estimate σ^2: ratio metrics (lift), Clustered SE (correlated observations)
    2. Increase N (pooled control group, split sample)
    3. Increase effect size (Triggering Experiments)
    4. Reduce variance (transform matrix and interleaving design)
    5. Stratification (post and at assignment)
    6. Regression with controls, CUPED
    7. Paired Design, Block Design
5. Observational Causal Studies
    1. Interrupted time series (ITS)
    2. Regression discontinuity design (RDD)
    3. Difference-in-Difference (DID)
    4. Propensity score matching (PS)

- Compare the means (lift, median, etc) between treatment and control
- Interpret the results considering type I and II errors

- Two principles to be considered during the whole process of experiments
- Need to guarantee internal validity
- Consider external validity when generalizing the results

- Improve sensitivity means using the smaller sample to achieve larger power
- Always a desire to improve the power given a sample size

- Mimic randomized controlled experiments using observational data

A/B Testing

- A/B testing is relatively new, particularly in China.
- My goal is to teach you how to approach and solve real-world problems effectively.
- It's important to recognize that there isn't a one-size-fits-all solution; rather, you should apply what you've learned to a range of situations.
- Deepening your understanding will take time and experience.
- Currently, there are fewer experts in A/B testing and causal inference compared to those specializing in machine learning and predictions within the industry.
- The shift towards data-driven decision-making—where machines are increasingly making decisions traditionally made by humans—is underway.
- This course is designed to equip you to be an active participant in this evolving landscape.

- Feel free to email me or make an appointment with me if I am of any help.
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  - https://www.shanhhuang.com/
- Course Website:
  - https://github.com/shanmit/Course---Digital-Experimentation-Methods-A-B-Testing/
- Thank you very much!