Attrition, Mediation, and Generalizability

1. Attrition: can’t observe the outcome for every individual in your experiment. Must consider how people come to have x values that may be used as comparisons. If subjects are lost from control group, then the apples-to-apples comparison may be lost. Important to consider conclusions when people opt out of being measured in an experiment.
   1. Types of attrition:
      1. Attrition by movement (e.g., because people want to move to places with less taxes)
      2. Attrition by survey nonresponse
   2. Detecting Attrition. On average, are people more or less likely to be observable in treatment or control?
      1. “Average treatment effect” on ability to measure the outcome. No (zero) average differential attrition can conceal big differential attrition.
         1. Code 1 or 0 outcome variable to determine if outcome was observable. Is the measurement rate of the outcome the same in treatment and control?
         2. Simple regression of response to survey on treatment assignment. On average, are people more or less likely to be observable in treatment or control? This test may detect some types of differential attrition.
      2. Balance on ex ante covariates across treatment groups
         1. Is there some indication that different groups were more or less likely to be observable differentially in treatment or control?
         2. In political example, look for differences in income or political party.
            1. Is there, on average, a similar likelihood of being a Democrat among those who answered the survey in both treatment and control?
      3. Differential attrition concealed because can’t measure (differential attrition due to treatment).
         1. Especially applies in political and commercial examples when people voluntarily agree to be measured. Treatment may change some peoples’ behavior.
         2. We may not be able to observe all the reasons why people chose to take or not to take our survey.
         3. Attrition can make us worried. If it happens randomly, it’s fine, but we don’t know if it’s actually random. Look and see if average attrition is different across groups. Differential attrition can be totally undetectable, even when it biases your conclusion.
   3. Preventing Attrition
      1. Conceal the purpose of the survey. Convince people to take the survey without knowing it is related to a treatment they have already received.
      2. Increase response rate overall. More likely to get more representative sample when response rate is higher.
      3. Secure commitment from subjects. Only do randomized treatment and control groups within those who have committed to take survey.
      4. Locate a subject pool that is unlikely to attrit.
      5. Consider other measurement strategies.
2. Mediation: why does a particular affect arise. Treatment may have not have a direct effect on Y. The mediator is an intervening variable the treatment changes that causes Y to change. Fundamentally unanswerable question.
   1. Asking questions is important!
      1. But there are limits to what we know, or even could know in many contexts.
      2. Maintain an eye for deeper understanding, but acknowledge where a usefully shallow understanding can suffice.
   2. Typical approach: once add in the mediator in the regression, does the original treatment coefficient go down? Analysis is typically biased. The treatment is no longer effective when we control for the mediator. Cannot determine if a particular mediator is responsible for why a treatment has an effect.
      1. Does not definitively establish that the mediator caused the treatment to lose effect.
      2. Mediator was not randomly assigned.
      3. Treatment may have affected other mediators.
      4. Other potential mediators correlated with the mediator that was measured.
      5. May see the same outcome with different mediators.
   3. Why mediation is difficult to study
      1. Mediation analyses are always suggestive, never definitive.
      2. Experimental estimates of indirect effects must affect only the mediator in question.
      3. In the social sciences, treatment may have several potential causal pathways.
      4. Mediators often aren’t directly measurable, such as thoughts or interests.
         1. Cannot be sure which mediators are being changed with treatment.
         2. Cannot be sure that all possible mediators have been measured.
      5. Causal heterogeneity: subjects are differentially affected by changes in X and M.
   4. Mediation usually isn’t critical but suggests more research.
      1. Mediation analyses can guide thinking and suggest hypotheses for future research, but will not be certain a particular mediator is the cause of why a treatment had an effect.
   5. Implicit mediation analyses
      1. Theory by looking for subgroup effects.
         1. Cannot be certain why a treatment had an effect.
         2. Tests theory to see how consistent they are.
3. Generalizability: any particular experiment is only guaranteed to speak to the particular units and particular context in which it was conducted. Many differences across people and areas that might lead us to different conclusions (e.g., heterogenous treatment effects).
   1. Generalizability of treatments:
      1. E.g., treatments first tested in research hospitals, with highly trained and educated staff, tend to be more effective than when tested in other hospitals. Research hospital doctors may be better at following protocol and managing patients with side effects; therefore, treatment is different in research hospitals compared to others.
   2. Results might change when you try an experiment with another population.
      1. People and partners most willing to try a new intervention may be most likely to benefit.
      2. Those least willing to give up something may benefit the most.
      3. There are many ways that a particular experiment’s results might differ across contexts.
   3. Perform other experiments to validate that your results would replicate in other circumstances.
      1. In general, we don’t know if the results generalize until we replicate.
      2. No experiment applies to all circumstances.
      3. With many experiments, you can start to build more general theories.