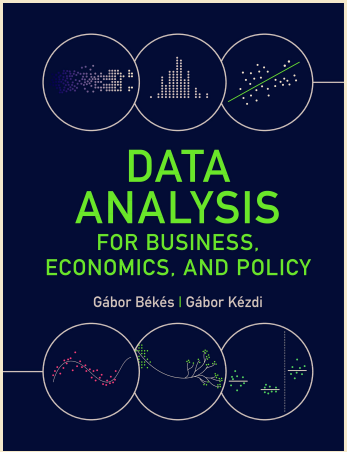
Békés-Kézdi: Data Analysis, Chapter 20: Designing and Analyzing Experiments



Data Analysis for Business, Economics, and Policy

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(remember) Controlled experiments

- The most powerful way to identify cause and effect relationships is conducting controlled experiments.
- Recall aspects of a well-defined causal question:
  - (1) the outcome (y) and causal (x) variables,
  - (2) to whom we want to establish he effect,
  - (3) what intervention should make the causal variable vary across observations,
  - (4) through what mechanisms we expect effect to take place.
- Controlled experiments collect data address all aspects.
  - Look at the right outcome and the right causal variable,
  - for observations that represent the ones we are interested in,
  - they vary the causal variable by interventions we are interested in,
  - and they rule out mechanisms we are not interested in.

Controlled experiments

- Controlled experiments allows for controlling variation in the causal variable
- Variation in the causal variable x is controlled by assigning values of x to the observations.
- This practice is called controlled assignment.
- By controlling assignment:
  - No self-selection: the value of x observations "receive" is not affected by the decisions of people who may be interested in the outcome.
  - No reverse causality by not letting the outcome y affect x in any way.
- If binary treatment x, observations are assigned to a treated and an untreated ("control") group by the experimenter.

Controlled experiments

- Well-controlled assignment of x results in very similar features for observations that are different in x.
- With a binary treatment, observations in the treatment group and observations in the control group are expected to have (on average)
  - the same values of Y(0)
  - same values of the treatment effect Y(1)-Y(0)

- Independence assumption of the potential outcomes framework is met.
- ATE will be identified and we can estimate ATE

Controlled Experiment types

- field experiments: aim to be as similar as possible to real-world decision situations
  - Test the impact of small loans in rural areas
- lab experiments: are carried out in an artificial environment, usually a computer lab
  - Test how people play games, react to incentives
- A/B tests aim to evaluate different versions of the same product
  - online presentation of an advertisement or a website.

RCT design and estimation

Randomization in controlled experiments

- Controlled assignment often involves randomization.
- Randomization is an assignment rule: it assigns different values of x to different observations.
- Random assignment rule is independent of all potential confounders.
- This independence is by design.
  - A well-executed randomization guarantees that features are very similar in groups with different values of the causal variable x, such as treated and control groups.
  - remember: ideal would be measuring the average TE, but instead we can have control and treated groups to be similar (on average)

Random Assignment in Practice

- A good assignment rule makes sure assignment is independent of everything that may affect the outcome.
- Computer-generated random numbers
- Some other independent rule, such day in month of birthday
- Lottery

The Experimental Setup

- Well-controlled experiments - average difference in y identify the average effect of x.
- With a binary treatment, the average difference in y between the treated and untreated group identifies the average treatment effect.
- Simple regression of $y^E = \alpha + \beta x$ plus a well-controlled experiment: Estimated ATE= β

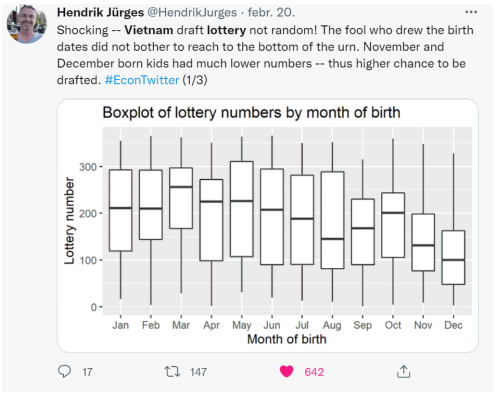
Randomization in controlled experiments

- Randomized controlled trial – RCT: controlled experiment with randomization as assignment rule.
- RCT are run to estimate the effect of an intervention
- Randomized assignment (treated units vs. control units) ensures independence.
- So average observed outcomes approximate well potential outcomes

Random assignment and checking balance

- Random assignment –> same distribution of all variables across groups
- Covariate balance (balance) = variables (covariates) are balanced across groups if their distribution is the same.
  - Binary: in the treated and control groups
  - Quantitative intervention, at all values
- Must check it - process of random assignment may be imperfect.
- A random rule leads to independence of potential outcomes in expectation.
  - Small probability, the actual assignment may lead to groups that differ .
  - Matters when groups are small.

Random Assignment in Practice: Unexpected challenge



See https://www.youtube.com/watch?v=aS3-HdthMVo&t=1s
via David Spiegelhalter "The Art of Statistics".

Case study: Working from home

- Working. From. Home. Uhhh.

Case study: Working from home

- Working. From. Home. Uhhh.
- Working from home four days a week makes employees more or less likely to quit the firm and whether it affects their performance.

Case study: Working from home

- Data is from employees of a travel agency in China.
- Bloom, Liang, Roberts, Ying "Does Working from Home Work? Evidence from a Chinese Experiment".
- Large travel agency in China.
  - Call center in Shanghai – booking hotels and airfare.
- Background: commuting time for employees was 80 minutes per day. Employees who were subjects of the experiment work in cubicles.

Case study: Working from home

- This is a field experiment.
- The intervention is making employees work from home four days a week.
- The subjects are employees of the firm.
- Two outcome variables:
  - quit firm (yes/no)
  - performance (number of phone calls).
- About half of the subjects were order takers - answer calls from customers and administer those calls.
- Performance – easy to measure – count number of phone calls processed.

Case study: Working from home

- 503 people volunteered for the experiment.
- Of them 249 qualified for the experiment
  - worked for 6 months + at the company
  - had broadband internet access + independent workspace at home

- 131 were assigned to work from home four days a week,
- 118 employees were assigned to continue work in the office.
- Selection was based on birthdays:
  - even date: work from home / odd: office.
- Consider the assignment rule random.

Noncompliance and intent-to-treat

- Suppose we have random assignment - RCT.
- Yet, the intervention may be less than perfect.
- It may not reach all subjects that were assigned to it.
- It may reach some subjects that were not assigned to it.

Noncompliance and intent-to-treat: Training program

- Training program form unemployed.
- Task is to see if training helps job prospects.

- Some of the unemployed subjects – assigned to participate –> decide not to participate or drop out early.
- Some of the subjects – assigned not to participate –> show up at training and may be allowed to participate.

Noncompliance and intent-to-treat: compliance

- When assignment to treatment and actual treatment do not conform we have noncompliance in the experiment.
  - assignment: what a subject should do
  - treatment: what a subject actually does
- The extent of compliance indicates how closely assignment and treatment are - on both directions
- Compliance is perfect if assignment and actual treatment are the same
- Compliance is imperfect if there is some noncompliance
- Non-compliance - any case when assignment and actual treatment differ.
  - Intervention does not get done is some locations

Noncompliance and intent-to-treat

- With imperfect compliance, 2 types of treatment effect.
- The effect of the treatment itself -> *ATE*
- The effect of being assigned to the treatment –> average intent-to-treat effect, *AITTE*.
- Estimate AITTE = average observed outcomes among subjects assigned to treatment - subjects assigned to non-treatment
- When compliance is perfect the $AITTE = ATE$
- When compliance is not perfect the $AITTE \neq ATE$
- Why not the same?

Noncompliance and intent-to-treat

- Imperfect compliance = hard to estimate the ATE even if random assignment to treatment.
- In reality, compliance is rarely random.
- Self-selection: compliance decision made by the subjects of the intervention.

Noncompliance and intent-to-treat

- Imperfect compliance = hard to estimate the ATE even if random assignment to treatment.
- In reality, compliance is rarely random.
- Self-selection: compliance decision made by the subjects of the intervention.
  - Those who comply with the assignment – different those do not to comply
  - ...in ways that are related to potential outcomes
    - how much they think they would benefit from the treatment.
- Self-selection to non-compliance = common cause confounder

- With random assignment but imperfect compliance
  - Good estimate of the AITTE
  - But can't get a good estimate of ATE.

Noncompliance and intent-to-treat

- If non-compliance - what can we do?
- Try to assess extent - difference between ATE and AITTE
- Care about AITTE - closer to what we shall expect from a similar intervention.

- Local average treatment effect (LATE) = the average effect on the subjects who comply with the assignment
- $LATE = AITTE/(p - q)$
  - p = proportion of treated among subjects assigned to treatment (comply)
  - q = proportion of treated among subjects assigned to non-treatment (not comply)
  - Under the Hood: 20.U1.

Estimation and statistical inference

- How to estimate ATE?
- Random assignment –> good estimate of ATE = difference between the average outcome in the treatment group and the non-treatment group
  - ATE if compliance is perfect – AITTE if compliance is imperfect.
- Regression or comparing means by a t-test.

$$y^E = \alpha + \beta x \tag{1}$$

- α is average y in the non-treatment group;
- β is the difference in the average outcome (y) between the treatment group ($x = 1$) and the non-treatment group ($x = 0$).

Including Covariates in a Regression

- Random assignment –> no need add variable for getting an unbiased estimate of ATE.

- In practice: multiple regressions that include other variables.
  - Indirect way of checking balance. Especially problematic vars.
- Get more precise estimates of the average treatment effect (smaller SE of β_1).
  - (DA2/Ch10) SE depends on R^2_{xz} = R-squared of the regression of x on the z variables.
- Estimate outcome y on treatment x and other variables (covariates) $z_1, z_2, ...$:

$$y^E = \beta_0 + \beta_1 x + \beta_2 z_1 + \beta_3 z_2 + \dots \tag{2}$$

Case study: Working from home

- In principle, all variables that affect potential outcomes need to be balanced.
- In practice, check balance only for variables measured. Typically: means.
- If very similar, we say the variables are balanced.
- Hypothesis test: difference mean in the treatment vs control group.
- Look at magnitude. Say, 1/10 SD difference = small.
- If some variables worrisome, we will add them as controls, but can carry on.
- If many variables, large differences: something went wrong or - if small sample - we were very unlucky

Case study: Working from home - balance

	Treatment mean	Control mean	Std.dev.	p-value of test of equal means
Number of observations	131	118	249	
Prior performance z-score	-0.03	-0.04	0.58	0.87
Age	24	24	4	0.85
Male	0.47	0.47	0.50	0.99
Secondary technical school	0.46	0.47	0.50	0.80
High school	0.18	0.14	0.36	0.38
Tertiary	0.35	0.36	0.48	0.94
University	0.02	0.03	0.15	0.91
Prior experience (months)	19	17	26	0.48
Tenure (months)	26	28	22	0.45
Married	0.22	0.32	0.44	0.07
Children	0.11	0.24	0.38	0.01
Age of youngest child	4.60	3.00	3.35	0.14
Rent apartment	0.24	0.20	0.42	0.44
Cost of commute (yuan)	7.89	8.34	6.96	0.63
Own bedroom	0.99	1.00	0.06	0.13
Internet	0.97	0.99	0.14	0.00
Base wage (yuan monthly)	1540	1563	161	0.23
Bonus (yuan monthly)	1031	1093	625	0.43

Case study: Working from home: balance

- A few cases p-values below 10% - (e.g. having internet access) no big deal
- Magnitudes of the differences - small.
- Most importantly, the two groups are virtually identical in terms of their performance score measured before the experiment.
- But there are some larger differences: married, have children. Need to pay attention.

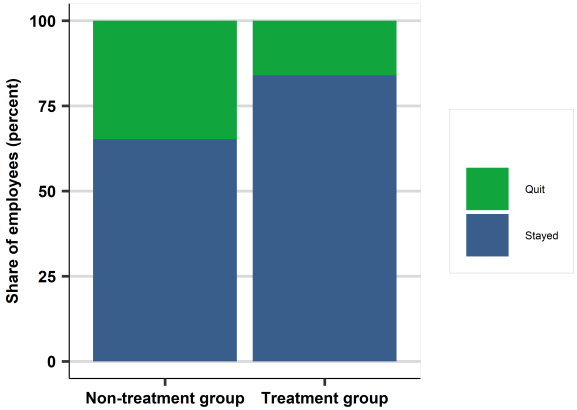
Case study: Working from home: compliance

- A small fraction ($< 20\%$) of employees in the treatment group re-assigned to office – changes in circumstances
- All employees assigned to the non-treatment group worked from the office through the duration of the experiment.
- Compliance in this experiment was imperfect.
- We can get the average intent-to-treat effect (AITTE).
- The degree of noncompliance was small.
- Thus AITTE is likely to be just a bit smaller than ATE.

Case study: Working from home

- Two outcomes: worker retention and worker performance.
- 16% in the treatment group quit, compared to 35% in the non-treatment group. The difference is 19 percentage points.
- Measure the performance of these 134 "order-takers" by the number of telephone calls they take.
- Number of phone calls taken, measured in thousands. The mean in the treatment group is 14, the mean in the non-treatment group is 10. The difference is 4 thousand.

Case study: Employee retention and quit rates in treatment and control group



- Employee retention and quit rates in the treatment group (working from home) and the non-treatment group (working from the office).
  - Stayed: remained employed for eight months;
  - quit: quit the company within eight months
- Source: working-from-home dataset. N=249

Case study: Working from home - effects

VARIABLES	(1) Quit job	(2) Phone calls (thousand)
Treatment group	-0.19**	4.04**
	(0.055)	(0.99)
Constant	0.35**	10.06**
	(0.044)	(0.75)
Observations	249	134
R-squared	0.047	0.113

Source: `working-from-home` dataset.

Case study: Working from home - Effects extended

VARIABLES	(1) Quit job	(2) Phone calls (thousand)
Treatment group	-0.19**	4.06**
	(0.056)	(0.96)
Married	-0.13	-5.44*
	(0.074)	(2.17)
Children	0.11	3.87
	(0.097)	(2.41)
Internet at home	0.18**	
	(0.036)	
Constant	0.19**	10.65**
	(0.056)	(0.76)
Observations	249	134
R-squared	0.055	0.168

Source: working-from-home

Case study: Working from home: internal validity

- Based on all the information, we can judge internal validity well.

Case study: Working from home: internal validity

- Based on all the information, we can judge internal validity well.
- Assignment was random.
- Compliance was imperfect, but only in the treatment group, and even here more than 80% of the subjects complied with the treatment.
- Spillovers are unlikely to be important in this experiment

Case study: Working from home: external validity

- Based on all the information, we can somewhat judge external validity .

Case study: Working from home: external validity

- Based on all the information, we can somewhat judge external validity .
- It had an actual impact, management changed practices
- Would it work for other employees? Yes for those who are like the ones in the experiment = applied
- Not necessary for all
- What can we say about other companies?

Case study: Working from home: external validity 2 (covid)

- WFH during covid

Case study: Working from home: external validity 2 (covid)

- WFH during covid
- WFH post-covid
  - Repeat similar RCTs
- Bloom, Han, Liang (2022) How Hybrid Working From Home Works Out (NBER WP)
  - "This paper evaluates a randomized control trial of hybrid on 1612 graduate engineers, marketing and finance employees of a large technology firm"
- Great deal of new evidence, growing lit
  - wfhresearch.com/research-and-policy/

Doing experiments: practicalities, validity

How to do an experiment? Practical advice.

Experiments in practice

- Design can be complicated
  - Multiple intervention "arms" (beyond 0,1)
  - "placebo" interventions
  - intensity of treatment, intention to treat versus actual treatment
  - Etc.
- Experiments need careful planning
  - Expertise needed
  - Results uninformative or misleading if poorly designed
- But analysis is relatively simple
  - Easy to carry out
  - Easy to communicate
- Practical problems = threats to internal validity

Spillover effects

- Intervention has spillover (or external) effect: its assignment to individual i affects some other individual j.
- As a result of spillovers the overall effect of the intervention may be different from the sum of its effects on treated individuals.
- In the presence of spillover effects analyzing the effects of interventions is more complicated.
- Sometimes it's easy to see potential spillover, in other cases not
  - Examples?

Example 2: Online ads - spillovers

- In the advertising example a spillover effect occurs if the fact that individual i sees the ad alters the spending behavior of someone else.
- May occur through communication between individuals: seeing the ad may make individual i convince a friend j to purchase the product.
- May happen through imitation: the ad makes individual i purchase the product, and this example may be followed by a neighbor j.
- Another potential spillover effect is substitution in case of fixed supply. With fixed supply an intervention that makes individual i purchase the product may prevent another individual j from purchasing the product.

Issues: Hawthorne, Placebo, John Henry

- Hawthorne effect
  - Both treated and non-treated individuals change behavior due to being observed
  - Are workers would become more productive in higher or lower levels of light - in the Western Electrics Hawthorne factory
    - Later proved that the effect was not there at all
- Placebo effect
  - Treated individuals change behavior due to being in treated (and not the treatment effect)
    - Important in many medical interventions
    - Placebo treatment arm - in medical experiments: both treated and comparison individuals receive pill - Only comparison individuals receive placebo
- John Henry effect
  - Non-treated individuals change behavior due to being in comparison group
    - E.g., they work harder
    - John Henry, a legendary US steel driver in the 1870s. When heard his output was being compared with that of a steam drill, worked so hard to outperform the machine.

Issues: Compliance (recap)

- Non-compliance
  - Not all units assigned to treatment actually finish treatment
  - Some units assigned to non-treatment end up being treated
- Intent-to-treat effect
  - Comparing those assigned to treatment and those assigned to non-treatment
    - Average intent-to-treat effects smaller than average treatment effects
- Cannot estimate treatment effect by comparing treated and non-treated
  - Even if assignment random
  - Actual treatment status affected by selection

Issues: Efficiency of Randomization

- Benchmark: simple randomization
  - Simple random draw of treatment indicator for each unit
- Cluster randomization
  - Clusters of units selected
    - E.g., villages
  - Lose efficiency / save on costs
  - May minimize spillovers
- Stratified randomization
  - First create strata, randomize treatment within strata
    - E.g., within same geographic unit, income category,
  - Gain efficiency / same costs

Designing A/B tests

Experimenting in Business

- Some firms do it
  - Most don't
  - Even though potentials are great
- Internet firms experiment a lot
  - randomly assign features of their service to different customers
  - A/B testing to study the effects of those features
- Few firms experiment with promotion activities
  - To see what increases sales most at lowest cost
- Even fewer firms experiment with incentive structures
  - To study what makes employees perform better

A/B Testing

- Two types of display options: A vs. B
- Users randomized to see either A or B
  - Randomize IP addresses
  - Randomization can be done within blocks
    - E.g., within countries, within days and hors, etc.
  - But showing different display to different users by characteristics does not substitute for randomization
    - E.g., different display by hour is not randomization
- Get average effect of display
  - The average treatment effect
- by comparing outcomes in groups A vs. B
- Question is effect of design so "compliance" is perfect
  - No need to worry about non-compliance

A/B Testing Example

- Obama campaign December 2007
  - https://blog.optimizely.com/2010/11/29/how-obama-raised-60-million-by-running-a-simple-experiment/
- Goal: design website to maximize donations
- 4 types of buttons, 6 types of media display
  - 24 options tested at once
- Optimal display increased sign-up
  - By 20%
  - = $60m extra donation

A/B Testing Example

- The winning design

Number of Subjects and Proportion Treated, Power

- Interested to run an experiment that can prove a difference or the lack of it.
- Need to design the experiment and make decisions.

Number of Subjects and Proportion Treated, Power

- Interested to run an experiment that can prove a difference or the lack of it.
- Need to design the experiment and make decisions.
- Two decisions that are relevant for all experiments:
  - (1) the number of subjects
  - (2) the proportion of subjects assigned to treatment.
- Affect the precision of the effect estimate.
  - More precision = smaller SE and a narrower CI.
  - More likely to detect a nonzero ATE by hypothesis testing.

Number of Subjects and Proportion Treated

- Testing = see if there is enough evidence in the data to reject a null hypothesis = a zero ATE. (Chapter 06)
- Decision to reject the null = avoid both a false positive and a false negative
  - In the general pattern represented by our data
- The likelihood of avoiding a false positive = level of significance;
- the likelihood of avoiding the false negative = level of power.
- A more precise effect estimate helps avoid both the false positive and the false negative

Number of Subjects and Proportion Treated

- To determine the precision we need, we fix a level of significance, (say 5%) and we want as high a power as possible.
  - Often 80% – not straightforward to interpret
- Low level of significance and a high power both require as precise an effect estimate as possible

Number of Subjects and Proportion Treated

- What proportion of the subjects should be assigned to the treatment group.
- 50% to make the estimates the most precise
- Could there be other consideration?

Number of Subjects and Proportion Treated

- How many subjects to include in the experiment, needs more work, and balance:
  - precision of the effect estimate
  - costs of carrying out an experiment.

- Power calculation - formula with some assumptions we make
- Binary outcome - need to assume the proportions in the two groups.
- Quantitative outcome, need to assume the difference in the means in the two groups and the standard deviation among all subjects

Number of Subjects and Proportion Treated

- It is a hypothesis testing setup
  - Mean outcome in the treated group be m_1,
  - Mean outcome in the untreated group be m_0.
  - Standard deviation of the outcome variable is σ.

$$H_0 : m_1 - m_0 = 0 \tag{3}$$
$$H_A : m_1 - m_0 \neq 0 \tag{4}$$

- Pick a 5% level of significance, and power at 80%
- Set the number of treated and untreated observations be same: $n_0 = n_1$. Total number of observations is $n = n_0 + n_1$

Number of Subjects and Proportion Treated

- We need some values from the normal distribution
  - 1.96 corresponds to 5% level of significance we set
  - 0.84 corresponds to the 80% level of power we set
- Standard deviation of the outcome variable is σ.
- Formula is

$$n = 4\sigma^2 \times \left(\frac{1.96 + 0.84}{m_1 - m_0} \right)^2 \tag{5}$$

- Can be used with any number of significance and power
- Has more complicated versions depending on distributional assumptions.

Number of Subjects and Proportion Treated

- Binary outcome, average=proportion.
  - Proportion of 1 among treated: r_1,
  - untreated observations r_0.
- The simplified test:

$$H_0 : r_1 - r_0 = 0 \tag{6}$$

$$H_A : r_1 - r_0 \neq 0 \tag{7}$$

- The overall proportion of 1s is $r = r_1/2 + 1_0/2$
- $\sigma = \sqrt{r(1-r)}$.

$$n = 4r(1-r)\left(\frac{1.96 + 0.84}{r_1 - r_0}\right)^2 \tag{8}$$

Case Study: Fine Tuning Social Media Advertising

- CEU promotion question and study setup
- A/B testing: Social media site, two versions of the ad
- Our budget: 2000 dollars + production cost + Massive work, 11 person-days

- Target audience: combination of filtering and look-alike
  - We filtered on age and country of residency and having a college degree + key-words, look-alike lists, and pages liked
- Two treatments: clicks and actions
- We need bigger sample sizes to measure small effect sizes, or to achieve high levels of certainty. Formation of assumptions is key

Case Study: Fine Tuning Social Media Advertising

- Stat: $p = 0.05$ (95% CI) $\alpha = 0.8$ for power (i.e., 20% chance of a false negative)
- Good case assumptions. :
  - Click through rate is 1%. Show ad 100 people, to get 1 click.
  - Conversion rate is 10%. Need 10 people to get an action (lead).
  - = Need 1000 impressions (show ad 1000 times) to get 1 action.
  - Assume one of the ads will be 30% higher conversion rate.
- Use power calculator, this means 400 thousand impressions needed.
- A worse case assumption
  - 20% difference, and 2000 impressions for one lead, so 0.0005 vs 0.0006
  - We would need 1.7 million impressions - appr 2000 USD.

Case Study: Fine Tuning Social Media Advertising

A version

B version

Case Study: Fine Tuning Social Media Advertising

- Reality:
- Ads were shown to 660,000 people, total impressions was about 2 million).
- 6400 unique visitors on the landing site
- 52 of them acted on it (ie gave some info)

Case Study: Social media campaign results

	Cost (dollars)	Target no. of impressions	No. of clicks	No. of actions	Cost per action (dollars)
A	1000	1 million	3323	32	31.25
B	1000	1 million	3128	21	47.62
Percent difference			6.23%	52.4%	
p-value			0.015	0.131	

Source: Summary data from the social media campaign.

Case Study: Fine Tuning Social Media Advertising

- 2 million impressions, 6461 unique visitors on the landing site
- 53 of them acted on it (ie gave some info)

- In terms of clicks, there is a small difference of 6.2% in favor of version A.
  - This difference is statistically significant at the 5% level
- The difference between the number of actions is large in relative terms – 52% in favor of version A.
  - = implied costs per action are lower for version A (47.62 vs 32.25.)
  - The number of actions is very small.
  - The difference not statistically significant = cannot reject the hypothesis that the two numbers are equal

Case Study: Fine Tuning Social Media Advertising

- We tested two messages, small difference. 1 in CEE wins in this region.
- Take-home message is that
  - If starting now, pick "A"
  - If already doing "B", we do not strong evidence to change to "A"

- Why this uncertainty?

Case Study: Fine Tuning Social Media Advertising

- We tested two messages, small difference. 1 in CEE wins in this region.
- Take-home message is that
  - If starting now, pick "A"
  - If already doing "B", we do not strong evidence to change to "A"

- Why this uncertainty?
- It turned out assumptions were very optimistic. In reality,
  - the click through rate = 0.3% (not 1%),
  - conversion rate = 0.8% (not 5%).
  - Overall 20x more impressions would have been needed
- = detecting a 20% difference require 30 million impressions, not 1.7 million. (If 50% difference, it's much less)

Case Study: Fine Tuning Social Media Advertising

- We tested two messages, small difference. 1 in CEE wins in this region. Cool.
- We measured the cost of a lead: 38 dollars (2000/53) - is it worth it?
  - Zero actual application...
- It's very hard to get certainty
- A/B testing may be very costly because differences are small, and need power.
- But we still can learn: large difference would come out, and even if not significant at 5% - still useful. Not proof, but suggestive.

Validity

- Internal validity
  - Whether RCT identifies causal effect of treatment
  - Here and now, in the actual context
  - If yes we say RCT has high internal validity
- External validity
  - The extent to which results of RCT generalize to other situations
  - Similar treatments not here or not now
  - If yes we say RCT has high external validity
- Sometimes trade-off
  - High internal validity more likely achieved in controlled situation
- Yet hard to generalize if low internal validity

Summary – controlled experiments

- Controlled experiments assign different values of x to observations in ways to
  - avoid selection and reverse causality,
  - control other aspects of the situation
  - avoid other confounders.
- With binary treatment assignment decides
  - which subjects in the experiment receive the treatment (the treatment group)
  - and which don't (the control group).
- Randomization
  - the most widely used assignment in business, policy and health applications
  - use of a rule that is known to be independent of all aspects of selection and other influences on outcomes.