SAMPLING AND STATISTICAL POWER

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Introduction

- What are we trying to do with impact evaluation?
- Determine if an intervention or treatment has had an effect and what that effect is
- Because we cannot have information on the same person/community/farm in two different states at one time (no parallel universes) need to draw on sampling theory-some but not all answers
- Start with randomization as benchmark (applies to other designs)

What are we trying to do?

We want to test the hypothesis that the effect size is equal to zero:

We want to test:

$$H_o : \text{Effect size} = 0$$

Against:

$$H_a : \text{Effect size} > 0$$

Can be done for different groups of individuals

Basic Setup

- Randomly assign subjects to separate groups, each of which is offered a different "treatment"
- After the experiment, we compare the outcome of interest in the treatment and the control group
- We are interested in the difference:

  Effect = Mean in treatment - Mean in control

  ***Example**: average voting rate in intervention villages vis-à-vis average voting rate in control villages*

  Change in production among treatment farmers compared to change in production of control group of farmers

Why randomize?

- Eliminates systematic pre-existing group differences (interest, wealth, entrepreneurship)
- However, randomization may produce experimental groups that differ by chance- not biases but ***random errors***

Bottom line: randomization removes bias, but it does not remove random noise in the data

Basic Setup cont.

- We do not observe the entire population, just a sample. ***Example***: *we do not have data for all villages of the country, but just for a random sample of them in treatment and control areas*
- We estimate the mean outcome of interest by computing the average in the sample. ***Example***: *we compute the average pregnancy rate for villages in the sample to estimate the mean pregnancy rate in the population*

Bottom line:

Estimated Effect = True Effect + Noise

Planning Sample Size for Randomized Evaluations

How large does the sample need to be to ***credibly*** detect a given effect size?

→ Measure with a certain degree of **confidence** the difference between participants and non-participants

Key ingredients: number of **units** (e.g. villages) randomized, number of **individuals** (e.g. households) within units, info on the **outcome of interest** and the **expected size** of the effect

Hypothesis Testing

"Ideal" property of any testing procedure:

- minimize disappointment , but
- allow for a minimum degree of error

→Avoid two types of mistakes

Type I Error

- **Conclude that there is an effect of treatment, when in fact there are no effect**

- SIGNIFICANCE LEVEL→ probability that you will falsely conclude that the program has an effect,

$$H_a : \text{Effect size} > 0$$

when in fact it does not.

- For policy need to be very confident in the answer you give: so set level fairly low. Common levels are: 5%, 10%, 1% (with 5% significance level can be 95% confident concluding that program had an effect.

Type II Error

Fail to reject that the program had no effect, when it fact it does have an effect

$$H_o : \text{Effect size} = 0$$

The power of a test is the probability that will be able to find a significant effect of the treatment if indeed there truly is one

Higher power is better since you are more likely to have an effect to report –avoid disappointment--and key for policy

Practical Steps

- Set a pre-specified **confidence level** (5%)
- Set a range of pre-specified **effect sizes** (what you think the program will do). What is the smallest effect that should prompt a policy response? Aka **minimum detectable effect**
- Decide on a sample size to achieve a given power (80% or 90%).
- Intuitively, the larger the sample, the larger the power. Power is a planning tool: one minus the power is the probability to be disappointed
- Budget…..

Practical Steps -- "magic formulas"

Proposition I:

There exists at least one statistician in the world who has already put into a magic formula the optimal sample size required to address this problem

Proposition II:

The rule has also been implemented for almost all computer software

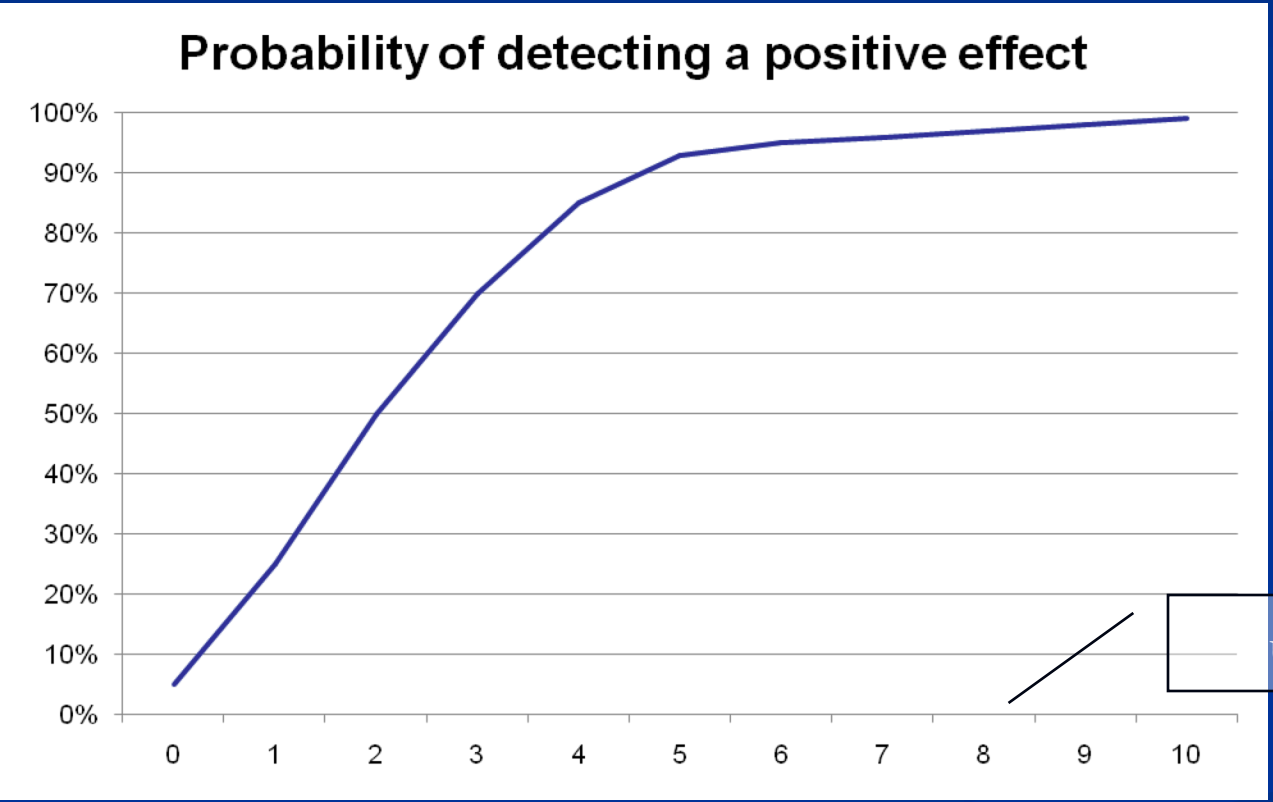
Not difficult to do, and only requires simple calculations to understand the logic (really simple!)

Picking an Effect Size

- What is the smallest effect that should justify the program to be adopted:
  - **Cost of this program vs the benefits it brings**
  - **Cost of this program vs the alternative use of the money**

- Common danger: picking effect size that are too optimistic—the sample size may be set too low

Hypothesis Testing, cont.



Sample size

General "rule": the sample size required is a function of:

- **Significance level** (often set to 5%)
- **Minimum detectable effect** – you set this
- **Power to detect it** (often set to 80%)
- **Variance of the outcome of interest** before the intervention takes place (derived from baseline data)
- **Clustering:** effect of clustering (derived from baseline data)

The Design Factors that Influence Power

- The level of randomization (clustering)
- Availability of a Baseline
- Availability of Control Variables & Stratification

Level of Randomization
Clustered Design

- Cluster (or group) randomized trials are experiments in which social units or clusters rather than individuals are randomly allocated to the intervention group

- **Examples**: first randomize **villages**, and then observe outcome variables at the **household** level. Or, in an education program, randomize **schools** and then look at **students**' achievement.

Level of Randomization Clustered Design (cont.)

- Cluster randomization provides unbiased estimates of intervention effects for the same reasons that individual randomization does

- However, the statistical power or precision of cluster randomization is less than that for individual randomization, and often by a lot!

Impact of Clustering

- The outcomes for all the individuals within a cluster may be correlated
  - All villagers are exposed to the same NGO
  - All patients share a common health practitioner
  - Inequality rates vary from village to village
  - The members of a village interact with each other
- The sample size needs to be adjusted for this correlation

  The more correlation between the outcomes, the more we need to adjust the standard errors

Practical implications

- *It is extremely important to randomize an adequate number of clusters.*
- The general result is that the number of individuals within clusters matters less than the number of clusters

- Think that the "law of large number" applies only when the number of clusters that are randomized increases

Availability of a Baseline

A baseline has three main uses:

- Can get information on the outcome of interest before the intervention is implemented
- Can check whether control and treatment group were the same or different before the treatment (this may turn out very useful in non-experimental settings)
- Can be used to stratify and form subgroups

Control Variables

- To improve precision or to ensure that specific groups can be analyzed (gender, ethnicity, certain crops) one can **stratify** experimental sample members by some combination of their baseline characteristics, and then randomize within each stratum

- Factors used for stratifying in social research typically include
  - geographic location,
  - demographic characteristics,
  - past outcomes

Control Variables (cont.)

- If the control variables explain a large part of the variance, the precision will increase and the sample size requirement decreases. This reduces variance for two reasons:
  - reduces the variance of the outcome of interest in each stratum, and
  - the correlation of units within clusters

- **Warning: control variables must only include variables that are not INFLUENCED by the treatment, i.e. variables that have been collected BEFORE the intervention**

Control Variables (cont.)

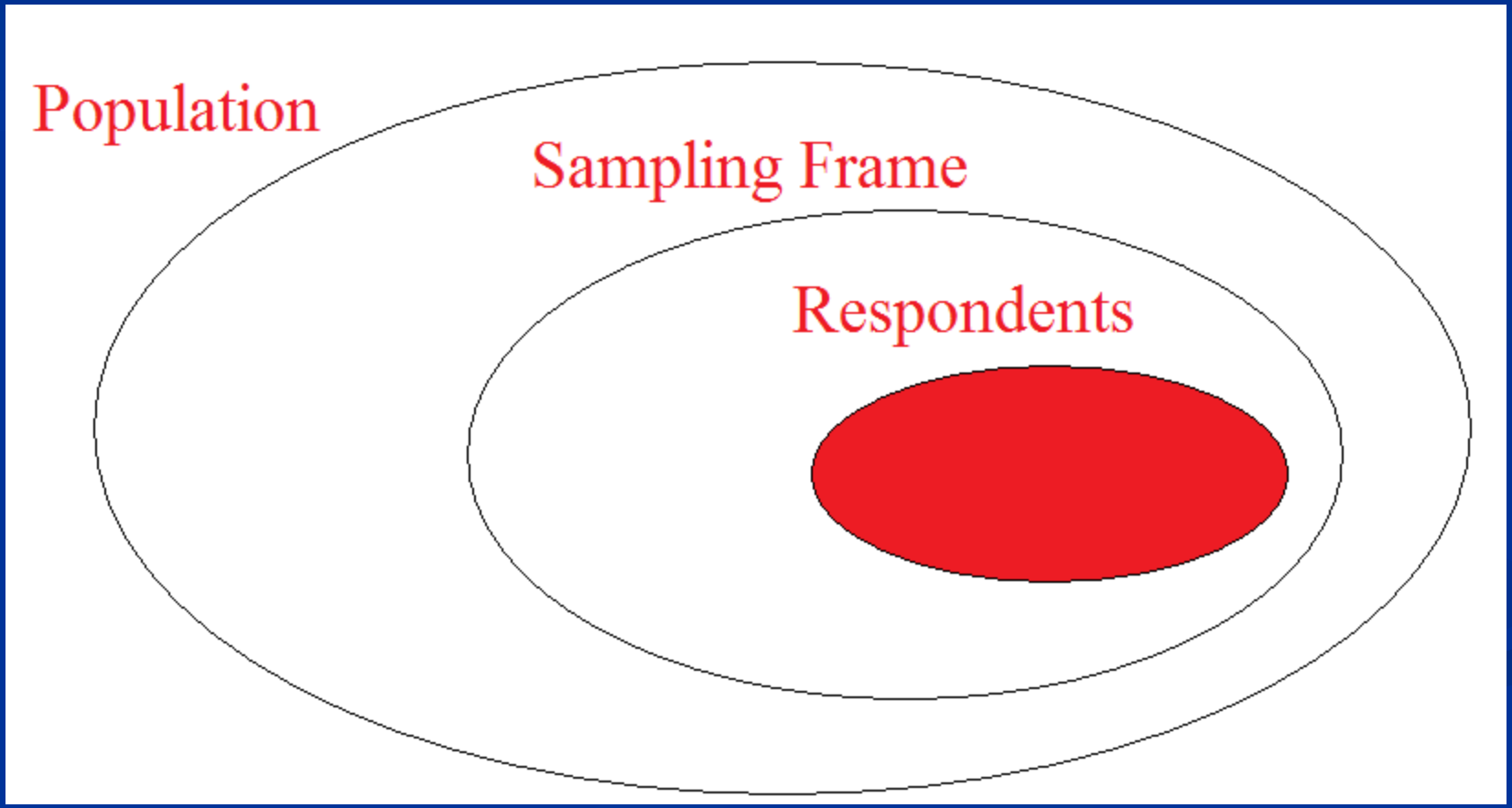
- What matters now for power is the residual variation after controlling for those variables… so just replicate the steps described above within strata

- It may help stratifying along dimension that we know from previous studies are important for the effects of the programme. **Example**: we might expect to have differential effects by gender or age groups

- This may help understand "non-response" rates

Non-response

Graphically

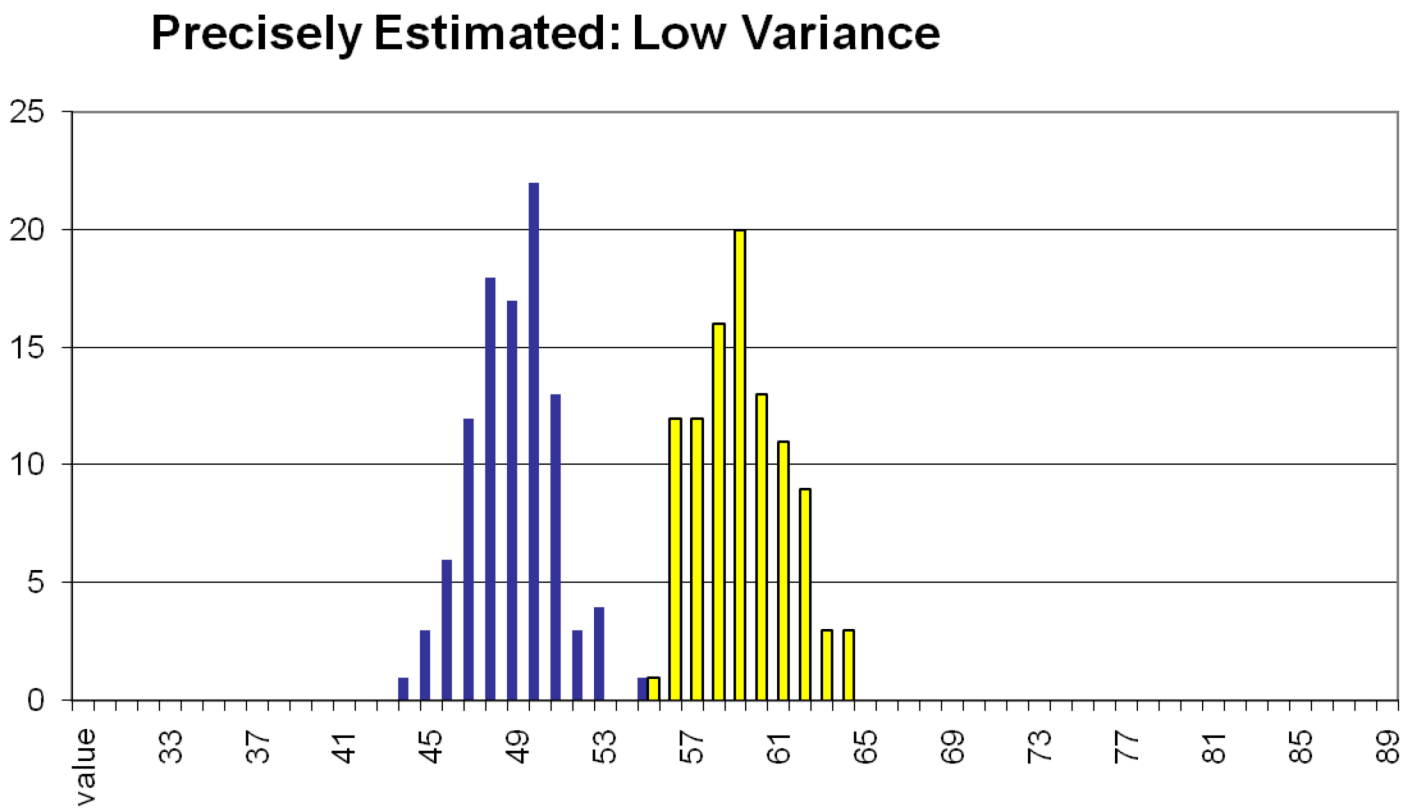


Summary

- Power calculations involve some guess work
- At times we do not have the right information to do it very well
- However, it is important to spend effort on them:
  - Avoid launching studies that will have no power at all: waste of time and money
  - Devote the appropriate resources to the studies that you decide to conduct (and not too much)
- Budget

Thank You
Merci
Obrigada

What do we mean by "noise"?



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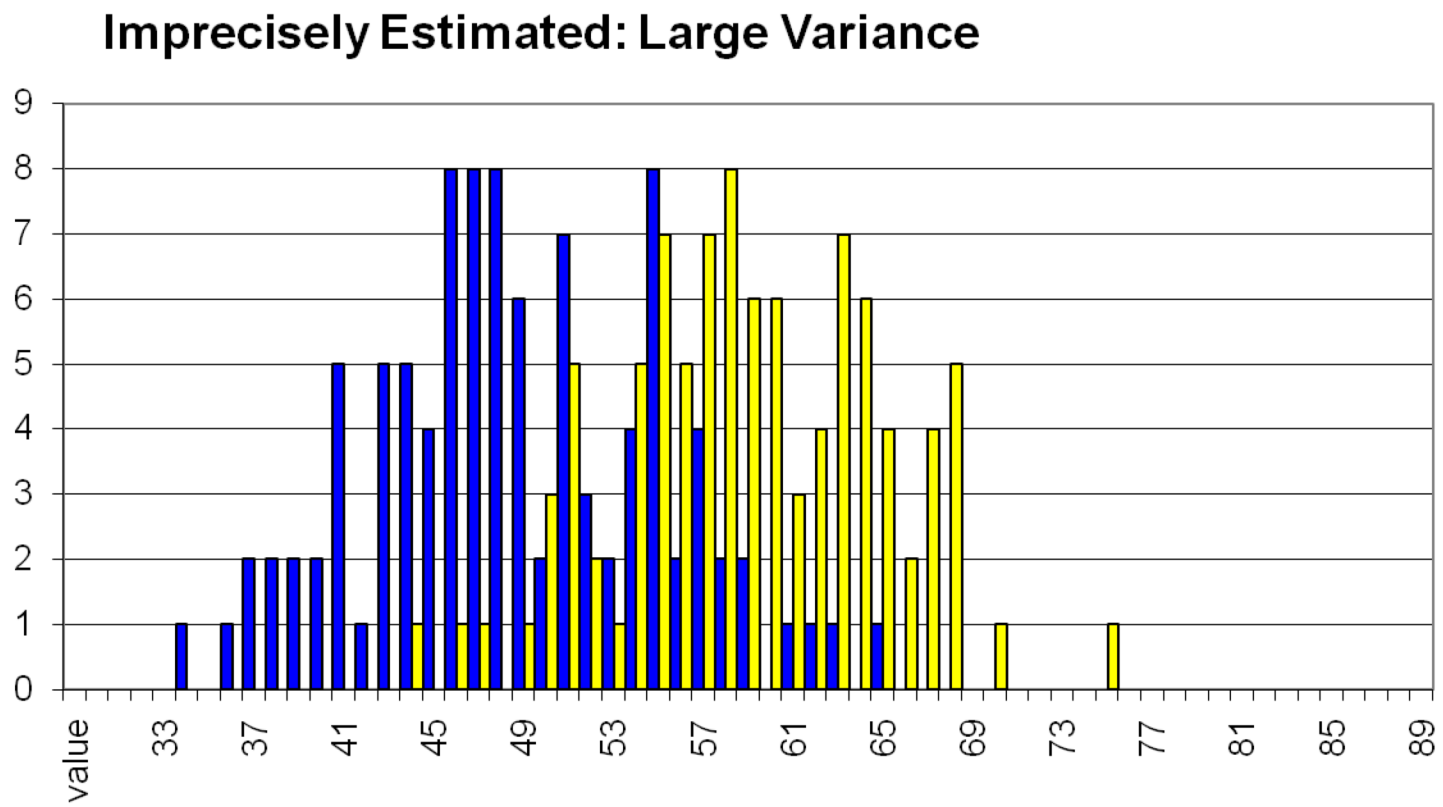

Relation with Confidence Intervals

- A 95% confidence interval for an effect size tells us that, for 95% of any samples that we could have drawn from the same population, the estimated effect would have fallen into this interval
- If zero does not belong to the 95% confidence interval of the effect size we measured, then we can be at least 95% sure that the effect size is not zero
- The rule of thumb is that if the effect size is more than twice the standard error, you can conclude with more than 95% certainty that the program had an effect

Standardized Effect Sizes (but this is a 2OP here)

- Sometimes impacts are measured as a standardized mean difference, for example when outcomes in different metrics must be combined or compared
- The standardized mean effect size equals the difference in mean outcomes for the treatment group and control group, divided by the standard deviation of outcomes across subjects within experimental groups