Gov 50: 8. Measurement: Survey Sampling

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Fall 2018

- 1. Today's agenda
- 2. The role of randomization
- 3. The power of randomization
- 4. Missing data in R

1/ Today's agenda

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- DataCamp 3: due tonight.

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- Next Thursday is a midterm review session run by TFs.

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2/ The role of randomization

The Literary Digest

Topics of the day

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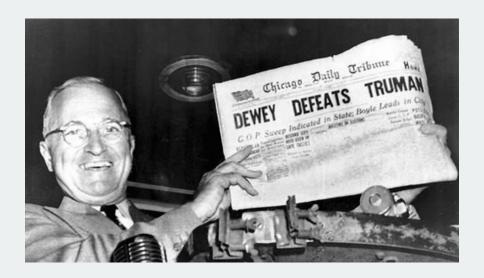
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- Selection bias: ballots skewed toward the wealthy (with cars, phones)
 Only 1 in 4 households had a phone in 1936.
- Nonresponse bias: people who respond are different than those who don't.
- Lesson: when selection procedure is biased, adding more observations doesn't help!

1948 Election



	Truman	Dewey	Thurmond	Wallace
Crossley	45	50	2	3
Gallup	44	50	2	4
Roper	38	53	5	4
Actual Outcome	50	45	3	2

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- Republicans easier to interview within quotas (phones, listed addresses, etc)

2020????



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- Random digit dialing:
 - Take a particular area code + exchange: 617-495-XXXX.
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 - Every phone number in America has an equal chance of being included in sample.

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 - Digital divide: rich vs. poor, young vs. old
 - Correct for potential sampling bias via statistical methods.

3/ The power of randomization

Why randomization works

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- Randomization of surveys creates two groups: the sampled and the unsampled.
 - Just like RCTs creating two groups: treatment and control.
- If coin flips decide who gets in the sample, then the sampled and unsampled groups should be identical, at least on average.

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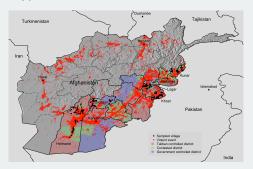
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 - Randomly choose villages from a list of all villages
 - ► Go to each village and randomly choose households.
- Question: do the sampled villages look representative?

Are the sampled villages representative?

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afghan.village <- read.csv("data/afghan-village.csv")
head(afghan.village)</pre>
```

```
##
     altitude population village.surveyed
        1959
                     197
## 1
## 2
        2426
                    744
                                        0
## 3
        2237
                    179
## 4
    1692
                  225
                                        0
## 5
    1928
                  379
                                        0
                    617
## 6
        1195
                                        0
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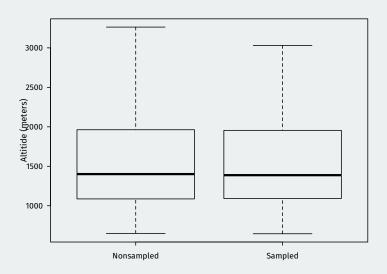
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Altitude distributions



4/ Missing data in R

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dim(na.omit(afghan))
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## [1] 2554 11
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• Contingency table: distribution cases are spread across two variables.

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• **Contingency table**: distribution cases are spread across two variables.

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table(ISAF = afghan$violent.exp.ISAF,
Taliban = afghan$violent.exp.taliban, exclude = NULL)
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## ISAF
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Contingency table: distribution cases are spread across two variables.

```
## Taliban
## ISAF 0 1 <NA>
## 0 1330 354 22
## 1 475 526 22
## <NA> 7 8 10
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## 0.03041 0.00635 0.00000 0.00000 0.06202
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Sensitive questions → non-response, social desirability bias

- Item non-response, like unit non-response, can create bias.
- More violent areas → more non-response:

```
## Helmand Khost Kunar Logar Uruzgan
## 0.03041 0.00635 0.00000 0.00000 0.06202
```

```
tapply(is.na(afghan$violent.exp.ISAF), afghan$province,
    mean)
```

```
## Helmand Khost Kunar Logar Uruzgan
## 0.01637 0.00476 0.00000 0.00000 0.02067
```

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## 0.01637 0.00476 0.00000 0.00000 0.02067
```

- Sensitive questions → non-response, social desirability bias
- racial prejudice, corruption, even turnout
- Do you support ISAF? What about Taliban?

Public nature of interviews



List experiments

• Script for the control group:

I'm going to read you a list with the names of different groups and individuals on it. After I read the entire list, I'd like you to tell me how many of these groups and individuals you broadly support, meaning that you generally agree with the goals and policies of the group or individual. Please don't tell me which ones you generally agree with; only tell me how many groups or individuals you broadly support.

Karzai Government; National Solidarity Program; Local Farmers

List experiments

• Script for the **treatment group**:

I'm going to read you a list with the names of different groups and individuals on it. After I read the entire list, I'd like you to tell me how many of these groups and individuals you broadly support, meaning that you generally agree with the goals and policies of the group or individual. Please don't tell me which ones you generally agree with; only tell me how many groups or individuals you broadly support.

Karzai Government; National Solidarity Program; Local
Farmers; ISAF (Taliban)

```
mean(afghan$list.response[afghan$list.group == "ISAF"]) -
  mean(afghan$list.response[afghan$list.group == "control"])
```

```
mean(afghan$list.response[afghan$list.group == "ISAF"]) -
   mean(afghan$list.response[afghan$list.group == "control"])
```

```
## [1] 0.049
```

Proportion of those who support ISAF:

```
mean(afghan$list.response[afghan$list.group == "ISAF"]) -
   mean(afghan$list.response[afghan$list.group == "control"])
```

```
## [1] 0.049
```

• Why does this work?

```
mean(afghan$list.response[afghan$list.group == "ISAF"]) -
   mean(afghan$list.response[afghan$list.group == "control"])
```

```
## [1] 0.049
```

- Why does this work?
 - Control group mean: avg number of control items

```
mean(afghan$list.response[afghan$list.group == "ISAF"]) -
  mean(afghan$list.response[afghan$list.group == "control"])
```

```
## [1] 0.049
```

- Why does this work?
 - Control group mean: avg number of control items
 - Treatment group mean: avg number of control items + proportion of people supporting ISAF.

Next time

• Summarizing the relationships between two variables.

Next time

- Summarizing the relationships between two variables.
- Make sure to have read QSS 3.5-3.6