

Survey research in the digital age

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Summer Institutes in Computational Social Science
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Schedule

- ▶ 9.00-9.45 Introduction & total error survey framework
- ▶ 9.45-10.15 Probability and non-probability sampling
- ▶ Coffee break
- ▶ 10.30-11.00 Computer-administered interviewing
- ▶ 11.00-11.30 Linking surveys to big data
- ▶ 11:30-13:00 Intro and begin group exercise
- ▶ Lunch (or Eisbach plunge)
- ▶ 14:00-15:45 Continue group exercise

Schedule

	Sampling		Interviews	Data environment
1st era	Area probability		Face-to-face	Stand-alone
2nd era	Random probability	digital dial	Telephone	Stand-alone
3rd era	Non-probability		Computer-administered	Linked

Warm-up exercise

Go to <https://forms.gle/AtdDu6hS8RiuhUWB6> and indicate your height in cm (e.g., “194”) and your sex. If you don’t know your height, or don’t want to tell, give an estimate or some plausible number.

Warm-up exercise

Let's have a look at

- ▶ ... the average height of the population (all of you)
- ▶ ... the average height estimated from a random sample
- ▶ ... the average height estimated from a non-random (but probability) sample

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Probability samples

- ▶ Probability sample (roughly): every unit from a frame population has a known and non-zero probability of inclusion
 - ▶ In the case of a simple random sample, this inclusion probability is n/N , with n being the sample size and N being size of population
- ▶ In practice, we rarely deal with a simple random sample
- ▶ However, if we know the inclusion probability, we can get an unbiased estimate of the population mean.

Probability-based estimation

Horvitz-Thompson estimator: the estimator for the population mean \bar{y} is

$$\hat{\bar{y}} = \frac{1}{N} \sum_{i \in s} \frac{y_i}{\pi_i}$$

where π_i is person i 's probability of inclusion. Verbally, this is a weighted sample mean where the weights are inversely related to the probability of selection.

Theory vs. practice

**Inference from
probability samples in
theory**

known information about
sampling
+ respondents
= estimates

Theory vs. practice

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Inference from probability samples in practice

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Theory vs. practice

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Inference from non-probability samples in practice

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Theory vs. practice

$$\hat{y} = \frac{1}{N} \sum_{i \in s} \frac{y_i}{\hat{\pi}_i}$$

where $\hat{\pi}_i = \frac{n_g}{N_g} \quad \forall \quad i \in g$ (estimated probability of inclusion)

Requires:

- ▶ auxiliary information (N_g)
- ▶ ability to place respondents in groups
- ▶ assumptions

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Theory vs. practice

- ▶ Not all probability samples look like miniature versions of the population—but, with appropriate weighting, probability samples can yield unbiased estimates
- ▶ How you collect your data impacts how you make inference
- ▶ Key to many adjustment methods is to use external information and make assumptions
- ▶ If external information is incorrect or assumptions are wrong, then you can make things worse (but it usually seems to make things better)

Back to warm-up

Back to the average height of your group:

- ▶ If I know the inclusion probability (e.g., 0.8 for males, 0.2 for females), it does not matter that the sample is non-probability
- ▶ If I know the frequency of males/females in the population (e.g., 0.5/0.5), I can build a weighted average ($0.5 \times \text{average males} + 0.5 \times \text{average females}$)
- ▶ However, I often don't know *why* more males participated than females; if I see more males than females in my sample, I have to *assume* that this imbalance is caused by sex and not something else
- ▶ In sum, I need assumptions to use sex as auxiliary information to estimate inclusion probability

Forecasting elections with non-representative polls

Wei Wang^{a,*}, David Rothschild^b, Sharad Goel^b, Andrew Gelman^{a,c}

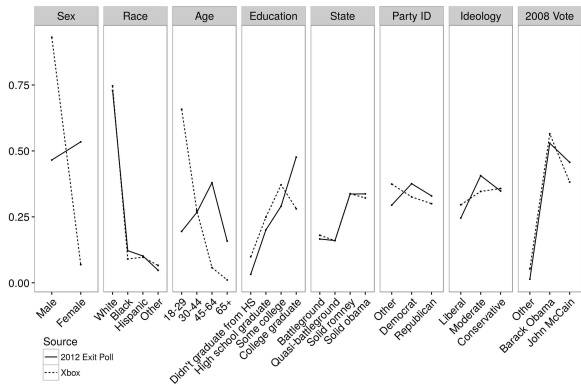
^a *Department of Statistics, Columbia University, New York, NY, USA*

^b *Microsoft Research, New York, NY, USA*

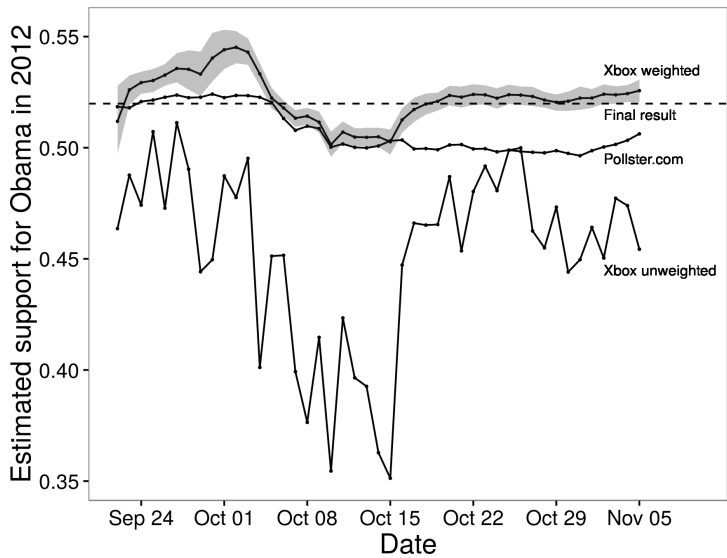
^c *Department of Political Science, Columbia University, New York, NY, USA*



<https://www.journals.elsevier.com/international-journal-of-forecasting/editors-choice-articles/forecasting-elections-with-non-representative-polls>



- ▶ about 750,000 interviews
- ▶ about 350,000 unique respondents



Online, Opt-in Surveys: Fast and Cheap, but are they Accurate?

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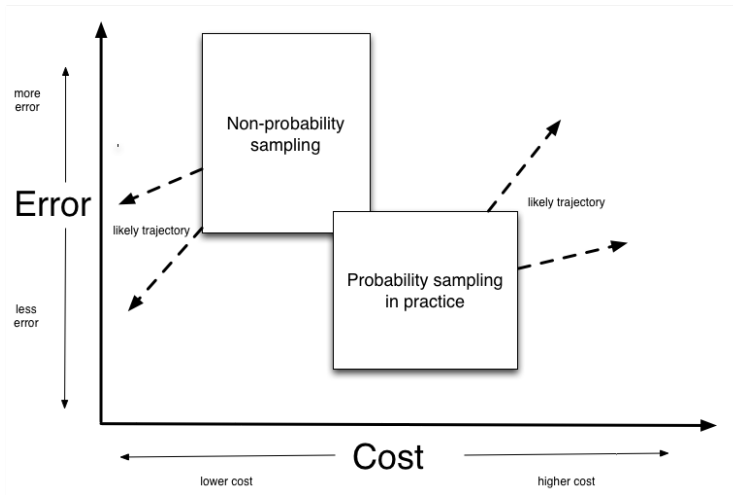
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<https://5harad.com/papers/dirtysurveys.pdf>

The future

... according to Matt Salganik



The future

RESEARCH SYNTHESIS: Are Nonprobability Surveys Fit for Purpose?

Jennifer Jerit
Professor
Department of Government
Dartmouth College

Jason Barabas
Professor, Department of Government
Director, Rockefeller Center for Public Policy and the Social Sciences
Dartmouth College

March 21, 2023

“In studies comparing the accuracy of probability and nonprobability samples in relation to government records, the former consistently outperforms the latter”

https://bpb-us-e1.wpmucdn.com/sites.dartmouth.edu/dist/d/2388/files/2023/05/JeritBarabas_NPS_Mar2023-1.pdf

The future

“Despite substantial drops in response rates since a prior comparison, the probability samples interviewed by telephone or the internet were the most accurate. Internet surveys of a probability sample combined with an opt-in sample were less accurate; least accurate were internet surveys of opt-in panel samples.”

<https://academic.oup.com/poq/article-abstract/82/4/707/5151369>

JOURNAL ARTICLE

The Accuracy of Measurements with Probability and Nonprobability Survey Samples: Replication and Extension

[Get access >](#)

Bo MacInnis, Jon A Krosnick ✉, Annabell S Ho, Mu-Jung Cho

Public Opinion Quarterly, Volume 82, Issue 4, Winter 2018, Pages 707–744, <https://doi.org/10.1093/poq/nfy038>

Published: 31 October 2018

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- ▶ Samples don't need to look like mini-populations
- ▶ Key to making good estimates is for estimation process to account for the sampling process
- ▶ There is not a bright-line difference between probability sampling in practice and non-probability sampling
- ▶ However, still a lot of debate about how non-probability samples really perform

Questions