

[Survey research in the digital age], [Probability and non-probability sampling], [Computer-administered interviews], [Combining surveys and big data], [Additions and extensions]

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- 1) Introduction
- 2) Observing behavior
- 3) Asking questions
- 4) Running experiments
- 5) Mass collaboration
- 6) Ethics
- 7) The future

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

Probability Samples

$$P(u_i) = \frac{p_i}{(N-1) \cdots (N-n+1)} \binom{N-1}{n-1} (n-1)! \\ + \sum_{j \neq i}^N \frac{p_j}{(N-1) \cdots (N-n+1)} \binom{N-1}{n-1} (n-1)! \frac{n-1}{N-1},$$

which upon simplification becomes

$$(19) \quad P(u_i) = \frac{N-n}{N-1} p_i + \frac{n-1}{N-1}, \quad (i = 1, 2, \dots, N).$$

Similarly, it may be shown that for this case

$$(20) \quad P(u_i u_j) = \frac{n-1}{N-1} \left[\frac{N-n}{N-2} (p_i + p_j) + \frac{n-2}{N-2} \right], \\ (i \neq j: i, j = 1, 2, \dots, N).$$

Non-Probability Samples



Probability Samples

unknown sampling process
weighting based on unverifiable assumptions

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- ▶ Not all probability samples look like miniature versions of the population
- ▶ But, with appropriate weighting, probability samples can yield unbiased estimates of the frame population

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- ▶ How you collect your data impacts how you make inference
- ▶ Focus on properties of estimators not properties samples

Main idea and equation in sampling and estimation:

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

where π_i is person i 's probability of inclusion

Sometimes called:

- ▶ Horvitz-Thompson estimator
- ▶ π estimator

Inference from probability samples in theory

respondents } estimates
known information about sampling }

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Inference from probability samples in practice

respondents } estimates
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Inference from probability samples in practice

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Inference from non-probability samples

$$\left. \begin{array}{l} \text{respondents} \\ \underbrace{\text{estimated information about sampling}}_{\text{auxiliary information} + \text{assumptions}} \end{array} \right\} \text{estimates}$$

Imagine that you want to estimate the average height of Princeton students.

- ▶ Assume 50% are male and 50% are female
- ▶ You stand outside Lewis Library and recruit a non-random sample of 60 Princeton students
- ▶ Males ($n = 20$): Average height: 180cm
- ▶ Females ($n=40$): Average height: 170cm

What is your estimate of the average height?

► sample mean = 173.3cm ($\frac{180*20+170*40}{20+40}$)

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- ▶ weighted estimate uses auxiliary information and assumptions
- ▶ How could this go wrong?

Forecasting elections with non-representative polls

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

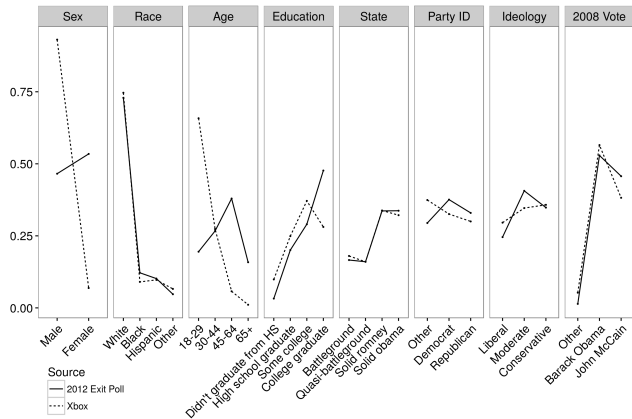
^a *Department of Statistics, Columbia University, New York, NY, USA*

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

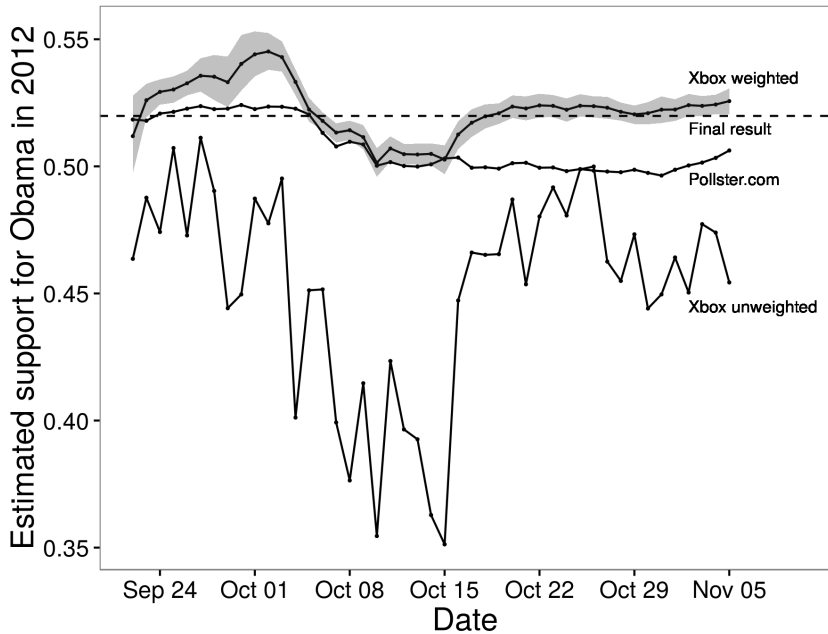
^c *Department of Political Science, Columbia University, New York, NY, USA*

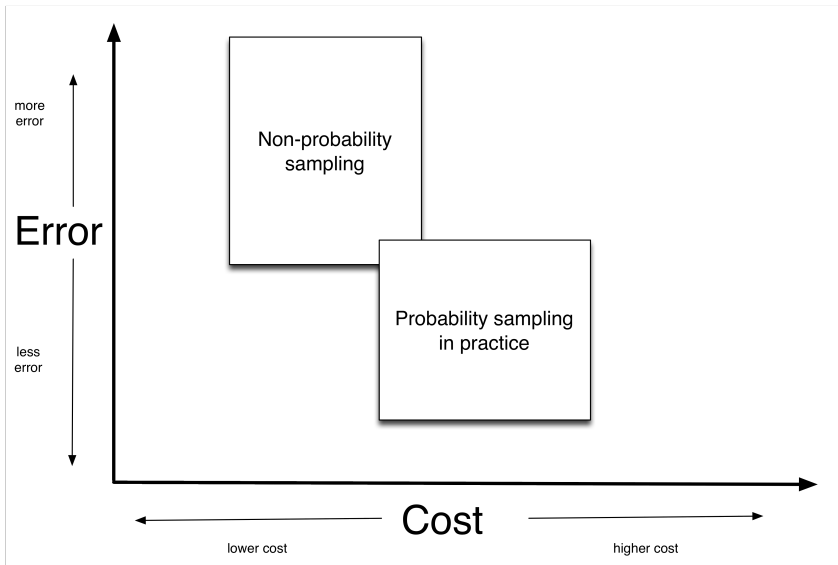


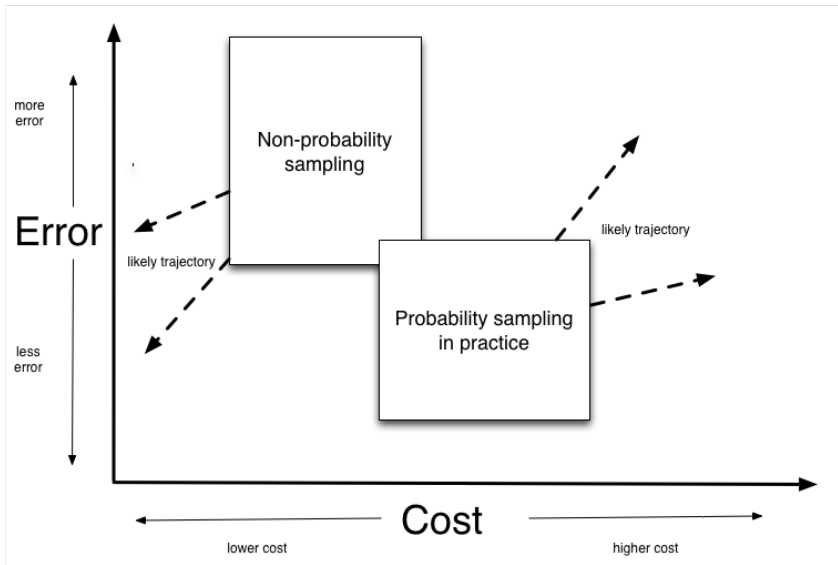
Wang et al (2015)



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







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Wrap-up:

- ▶ 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
- ▶ To learn more: Lohr (2009) or Sandal et al (2013)

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