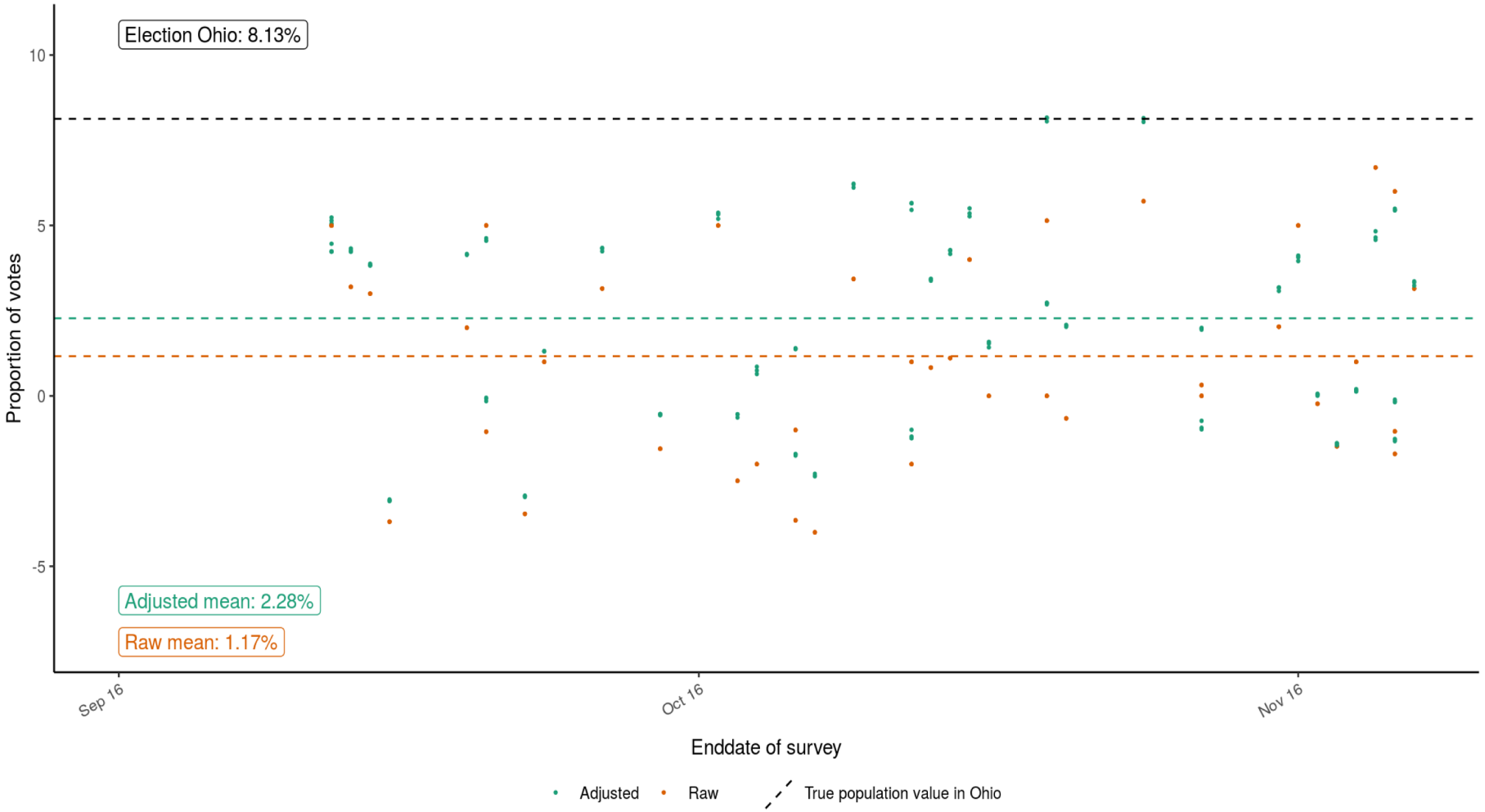
Survey data analysis
Week 49:
“Inference for non-probability samples”

Today

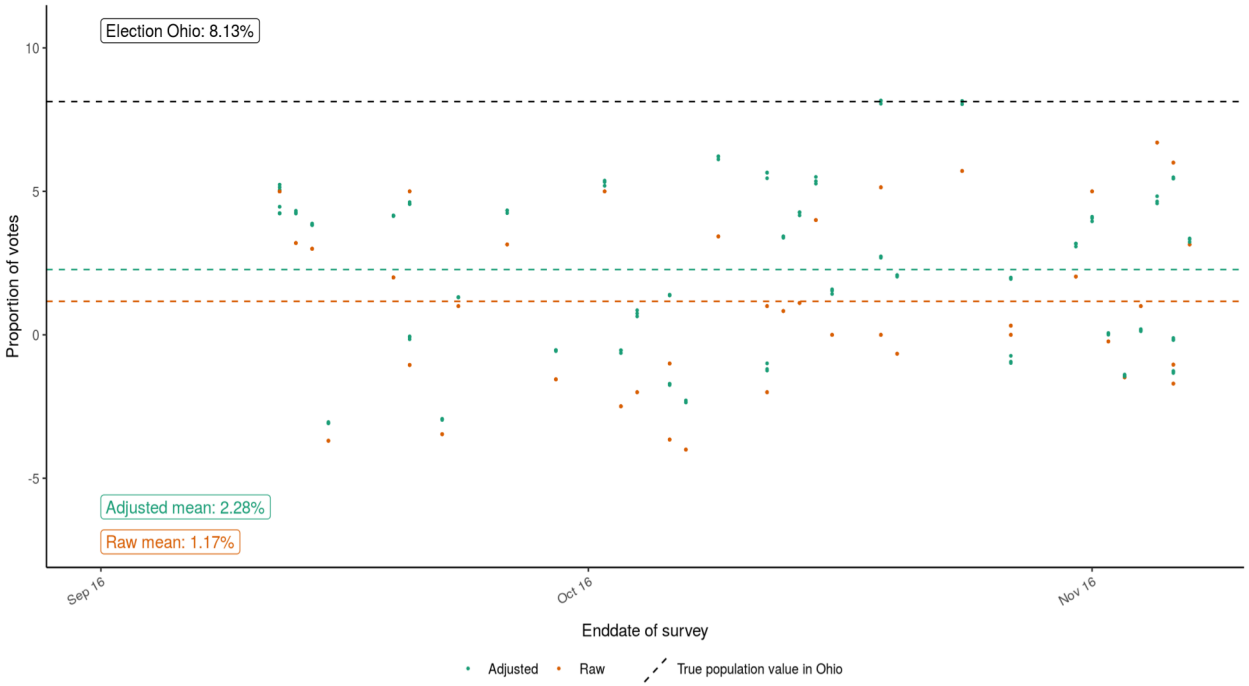
- Lecture
- Inference ‘competition’

Back to week 37 (1)



See: https://utrecht-university.shinyapps.io/SDA_shinyelectionbias/

Back to week 37 (1)



- Adjustments only help a bit on average
- For individual polls they sometimes make matters worse!

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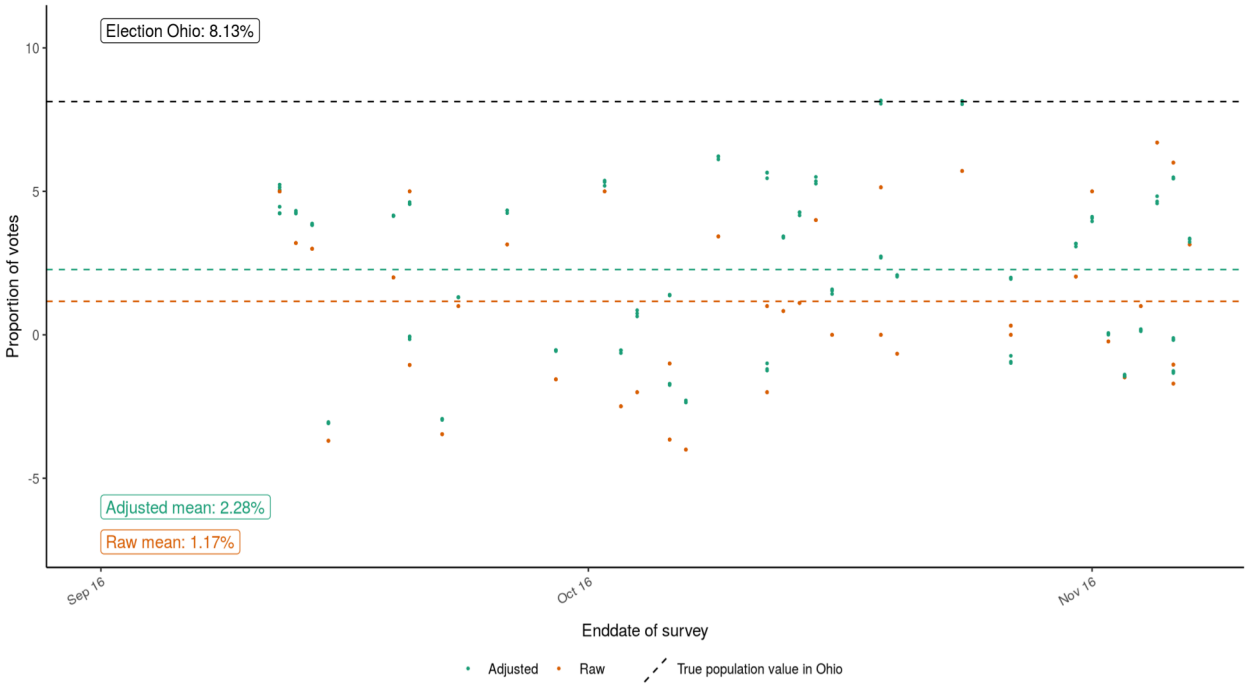
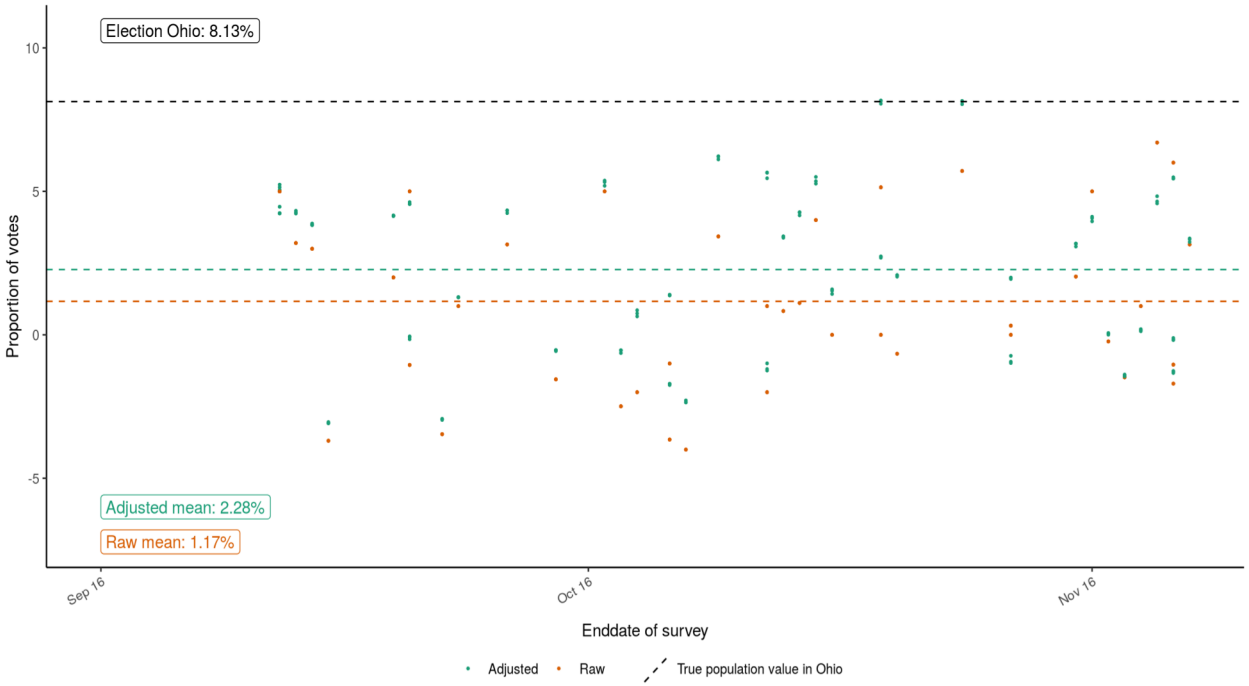


- Adjustments only help a bit on average
- For individual polls they sometimes make matters worse!
- Grade of pollster/ sample size/ population dont make the difference

We have an inference problem



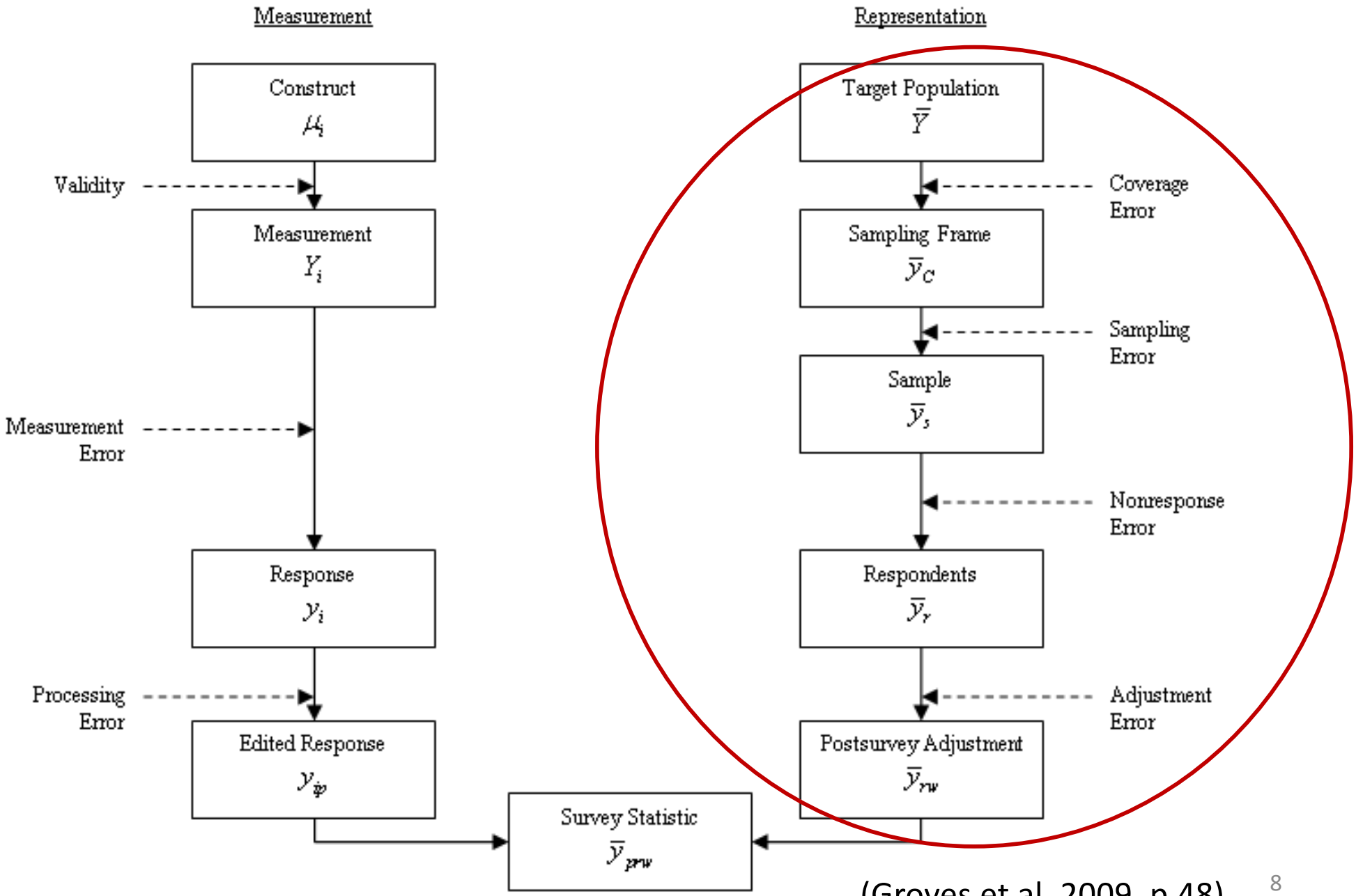
- Adjustments only help a bit on average
- For individual polls they sometimes make matters worse!
- Grade of pollster/ sample size/ population dont make the difference
- Problems with weighting
- A lot of polls are **not** probability based

Three articles today

- Cornesse et al (2020)
- Mercer et al (2018)
- Meng (2018)

What are the differences between their views?

Selection bias vs. TSE



(Groves et al. 2009, p.48)

Cornesse et al (2020)

- Non-probability surveys do worse than probability ones
  - Fit for purpose
- In what situation is a non-probability sample not too bad? (in pairs – 3 minutes)
  -
  -
  -

Cornesse et al (2020)

- When is a non-probability sample not too bad?
  - in change estimates?
  - (regression models)?
  - When controls are accurate (quota)
- Global adjustment approaches
  - i.e. Conceptualize as design-based
- Estimate-specific approaches
  - Later in lecture examples)

Mercer et al (2018)

- Three conditions for inference (p252)
  - Exchangeability
    - Do we have all relevant X covariates that (could) explain selection bias?
  - Positivity
    - Do we have all subgroups?
  - Composition
    - Can we match sample to the population?
      - Calibration or other weighting techniques

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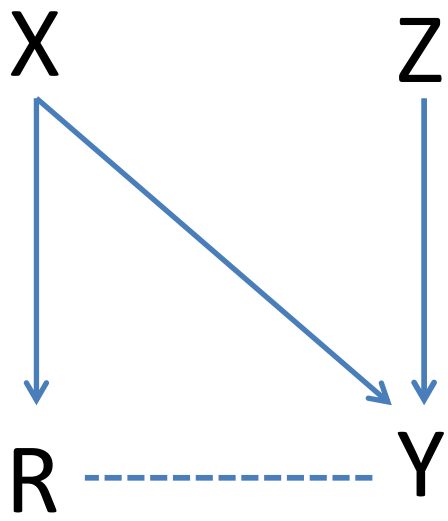
Can you apply these terms to the missing data diagrams? (2 min)



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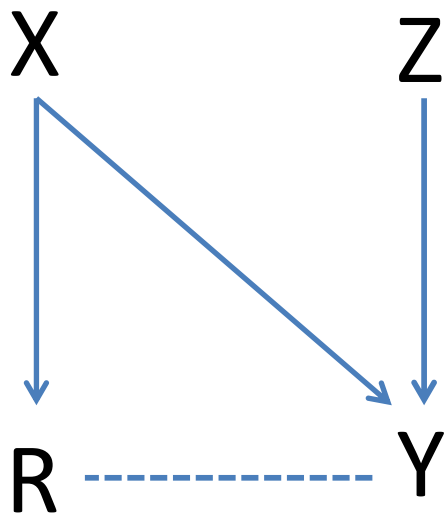

Inference: perspectives from other fields

- Natural sciences
  - Laws of nature: gravity works everywhere
  - Representation error not an issue
- Social sciences broadly
  - We need descriptives about our population and models about the world
    - External validity
    - More sociological
  - We want to test causal mechanisms
    - Internal validity
    - More psychological

Mercer et al (2018)

- Experiments
  - Strong ignorability (random assignment)
    - Exchangeability and
    - Positivity
  - Transportability: composition?
    - Can we match sample to the population?
    - Not considered an issue in inference
      - WEIRD samples

Mercer et al (2018)

- Design-based surveys
  - Random samples leads to ignorability
    - Exchangeability and
    - Positivity
  - And to transportability
    - Only sampling error
- Nonresponse and coverage error
  - Weighting fixes exchangeabilty
  - Positivity assumed (subgroups are al there)

Mercer et al (2018)

- Non-prob surveys and what to do?
  - Exchangeability (we need the right X vars)
  - Positivity (we need to have all subgroups
  - Composition

Meng 2018 – linking data quality,quantity

- ρ(R,G): correlation between selection bias (R) and variable of interest
- **σ**(G): variation in population of variable of interest
  - E.g. If everyone votes for Clinton, no problem
- Data quantity: $\sqrt{\frac{1-f}{f}}$
  - f=sampling fraction from population.

$$\overline{G}_n - \overline{G}_N = \underbrace{\rho_{R,G}}_{\text{Data Quality}} \times \underbrace{\sqrt{\frac{1-f}{f}}}_{\text{Data Quantity}} \times \underbrace{\sigma_G}_{\text{Problem Difficulty}} .$$

  - P. 690 (eq 2.3)

Meng 2018 – linking data quality,quantity

- R mechanism (response)
  - Design based
    - Sampling probabilities are known
    - Nonresponse propensities are modeled.
  - Non-probability: selection probabilities are unknown
- G: estimate of interest (e.g. a mean)
  - Y in missing data literature

$$\overline{G}_n - \overline{G}_N = \underbrace{\rho_{R,G}}_{\text{Data Quality}} \times \underbrace{\sqrt{\frac{1-f}{f}}}_{\text{Data Quantity}} \times \underbrace{\sigma_G}_{\text{Problem Difficulty}} .$$

- If correlation [R,G] = 0, no problem with any data
- If R does not vary over elements, no problem

Meng 2018 – final

When can we draw inferences for Big Data (non-probability samples)?

1. Data quality: ρ(R,G): 0
   - design based philosophy
   - Quality and quantity are independent (?)
2. Data quantity: f very large (close to 1)
   - Big data philosophy
   - Quality and quantity negatively correlated?
3. **σ**(G): very small

$$\overline{G}_n - \overline{G}_N = \underbrace{\rho_{R,G}}_{\text{Data Quality}} \times \underbrace{\sqrt{\frac{1-f}{f}}}_{\text{Data Quantity}} \times \underbrace{\sigma_G}_{\text{Problem Difficulty}} .$$

Now to practice

- Exchangeability (Mercer), or ρ(R,G): 0 (Meng)
- positivity is a design feature

Solutions

- 1.Global correction methods
  - Pseudo design based estimation (Elliott & Valliant 2017)
- 2. Estimate-specific methods
  - Calibration (Little, 2004)
    - non-prob -> probability
  - Superpopulation modeling (e.g. Elliott & Valliant, 2020)
  - Mass imputation (Yang and Kim, 2020)
- 3. Sensitivity analyses
  - Meng: for ρ(R,G)
  - Pattern mixture models for NMAR (e.g West 2020)

1. Pseudo design based

non-probability based

gender	age	education	health	Fav ice
0	34	1	5	vanilla
1	54	2	5	lemon
1	12	3	4	Choc
1	56	3	5	vanilla
0	87	4	2	strawb
1	45	5	3	zabaione
1	67	6	4	lemon
1	23	6	5	straccia
0	16	2	5	vanilla
1	24	4	4	straccia
1	56	2	4	straccia
1	78	3	2	vanilla

Taste	percentage
Vanilla	33%
Lemon	16%
Straccia	25%
Zabaione	8%
Strawberry	8%
Chocolate	8%

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0	16	2	5	vanilla
1	24	4	4	pear
1	56	2	4	straccia
1	78	3	2	vanilla

Other Probability based survey

gender	age	education	health	P(Response)
0	34	1	5	,24
1	54	2	5	,44
1	12	3	4	.23
1	56	3	5	.56
0	87	4	2	,36
1	45	5	3	.56
1	67	6	4	.44
1	23	6	5	.33
0	16	2	5	,32
1	24	4	4	.43
1	56	2	4	.42
1	78	3	2	.43

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0	34	1	5	,24	vanilla
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1	24	4	4	.43	straccia
1	56	2	4	.42	straccia
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Taste	Raw percentage	Weight (1/p)
Vanilla	33%	1/.39
Lemon	16%	1/.44
Straccia	25%	1/.39
Zabaione	8%	1/.56
Strawberry	8%	1/.36
Chocolate	8%	1/.23

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Taste	Raw percentage	Weight (1/p)	Weighted %
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Straccia	25%	1/.39	24%
Zabaione	8%	1/.56	6%
Strawberry	8%	1/.36	9%
Chocolate	8%	1/.23	14%
Ave		.40	

2. Estimate specific methods

2.1 Calibration (Little, 2004)

2.2 Superpopulation modeling (e.g. Elliott & Valliant, 2020)

2.3 Mass imputation (Yang and Kim, 2020)

2.1 Calibration

- Conduct a large nonprobability sample
  - Small s.e., large bias(?)
- Conduct a small probability based sample
  - Large s.e., small bias
- Weight non-probabity based -> prob based
  - Small bias (?), small s.e.
  - You can use lots of survey questions, because you conduct 2 surveys
  - Expensive, time consuming

2.2 Superpopulation modeling

- Non-probability based surveys don't use sample frames
  - We can rake or calibrate to population statistics:

    gender, age, region, ethnicity, income, etc…
- Idea is to collect more population statistics
  - Netflix subscription, voting Behavior, customer of a company, member of organization, ….

2.2 Superpopulation modeling

- Approach by Mercer (2017)
  - Netflix subscription? Voting Behavior, customer of a company, member of organization
- i.e. More elaborate weighting

Topics and corresponding benchmarks

Topic	Benchmark
Civic engagement	How often talks with neighbors
	Trusts neighbors
	Participated in a school group, neighborhood, or community association
	Volunteered in past year
Family	Marital status
	Presence of children in household
	Household size
Financial	Employment status
	Home ownership
	Family income
	Household member received food stamps
	Health insurance
Personal	Lived in house or apartment one year ago
	Active duty military service
	U.S. citizenship
	Gun ownership
	Smoking
	Food allergies
Political engagement	Voted in 2012
	Voted in 2014
	Contacted or visited a public official in past year
Technology	Tablet or e-reader use
	Texting or instant messaging
	Social networking

Note: See Appendix D for the source of each benchmark, the question text, the response categories, the benchmark estimate, and additional notes.
"For Weighting Online Opt-In Samples, What Matters Most?"
PEW RESEARCH CENTER

Source:https://www.pewresearch.org/methods/2018/01/26/reducing-bias-on-benchmarks/

2.3 Mass imputation

- We know the population distribution:
  - Gender, age, education, income, region, etc.
- In some cases we have frame data
- Why not impute **the whole population**?

Mass imputation

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  - Gender, age, education, income, region, etc.
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- Why not impute the whole population?

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1	56	2	4	straccia
1	78	3	2	???
1	56	4	5	???
….	…	…	..	???
You have X million rows, only X thousand of thesehave Y				

3. Sensitivity analyses

- Cf Meng (2018)
- Pattern Mixture modeling
  - Enter an additional parameter in the model (e.g a selection bias parameter)
  - This parameter can take different forms
    - Covary with Y and all other parameters
  - Simulate
  - Similar to Heckman selection models.

See Andridge, R. R., & Little, R. J. (2011). Proxy pattern-mixture analysis for survey nonresponse. *Journal of Official Statistics*, *27*(2), 153.

Exercise (class + THE)

- Competition!
  - Three non-probability samples
  - Sample size 30.000
  - June/July 2016
  - You get 15.000 cases
  - And a superpopulation dataset (Mercer, Lau & Kennedy, 2018)
- Goal: adjust your sample:
  - Choose your variables
  - Calibrate, rake, impute?
- Prize: eternal fame and a survey related present

Next week

- Lecture on “designed big data”
- Keep working on your group assignments
- In two weeks -> final meeting
  - Prepare an online document that should be readable in 6 minutes
    - Video, wiki, website….
  - Hand in December 10, 17:00
  - Review 1 presentation of other group and prepare 3 questions.

More reading?

- Andridge, R. R., & Little, R. J. (2011). Proxy pattern-mixture analysis for survey nonresponse. *Journal of Official Statistics*, *27*(2), 153.
- Chen, S., Yang, S., & Kim, J. K. (2020). Nonparametric Mass Imputation for Data Integration. *Journal of Survey Statistics and Methodology*.
- Elliott, M. R., & Valliant, R. (2017). Inference for nonprobability samples. *Statistical Science*, *32*(2), 249-264.
- Kim, J. K., Park, S., Chen, Y., & Wu, C. (2018). Combining non-probability and probability survey samples through mass imputation. *arXiv preprint arXiv:1812.10694*.
- Rafei, A., Flannagan, C. A., & Elliott, M. R. (2020). Big Data for Finite Population Inference: Applying Quasi-Random Approaches to Naturalistic Driving Data Using Bayesian Additive Regression Trees. *Journal of Survey Statistics and Methodology*, *8*(1), 148-180.
- Valliant, R. (2020). Comparing alternatives for estimation from nonprobability samples. *Journal of Survey Statistics and Methodology*, *8*(2), 231-263.