Lecture 14: Missing Data

Naijia Liu

March 19 2024

Logistics

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- **By April 4th,** mandatory OH with Naijia, Jeremiah or James, per group.

  We'd like to hear about your idea and dataset.
- If you are still looking for data:

  Run `data()` in `R-studio`.

  These are built-in and cleaned datasets!

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- What was the CO2 amount of every country in 1990?

  Governments did not document the data / chose not to report (countries want to hide their CO2 omission).

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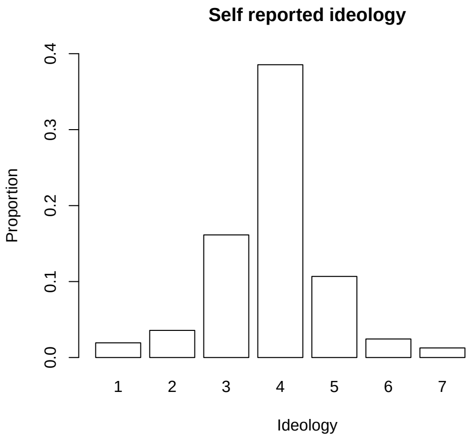
- What was the CO_2 amount of every country in 1990?

  We want to be able to study all types countries.

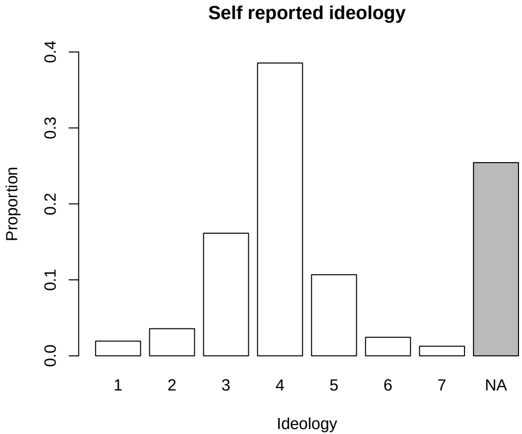
Why is missing data a problem?

- Survey questions to Chinese respondents: what is your ideology?
  - Anti China Communist Party respondents self censor, fearing consequences.



Why is missing data a problem?

- Survey questions to Chinese respondents: what is your ideology?
  - Anti China Communist Party respondents self censor, fearing consequences.
  - What if we completely miss a type of respondents in our analysis?



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  - Imagine spilling coffee onto the data sheet.
  - Randomly choose Chinese respondents to refuse to answer the ideology question.
  - Listwise deletion can deal with MCAR.

    i.e get rid of those who refused to answer the ideology question.

Missing Completely at Random

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  People with extreme ideology may feel insecure to reveal it.

Missing Completely at Random

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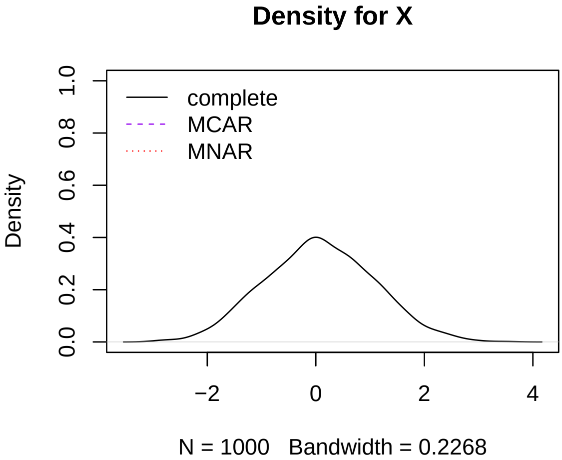

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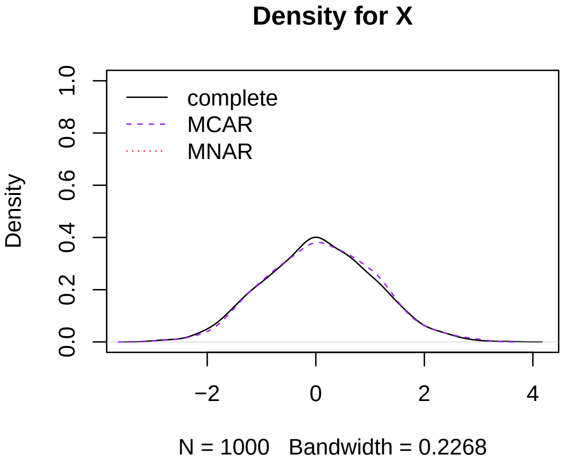

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  - Conditioning on observables, missing values and observed values are similar in general.
  - **Conditioning on all other variables in the dataset (such as age, gender, education), missing ideology answers are similar to observed responses, on average.**

Missing at Random

- Missing at random is more plausible than missing completely at random.
- We allow missing values to be different from observed values. The differences go away after taking into consideration of the observed variables.
- This indicates that we can utilize observed info to **impute** missing values.

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- Data is now complete.

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4. The missing values for "var" are then replaced with predictions (imputations) from the regression model.
5. Steps 2–4 are then repeated for each variable that has missing data.
6. Steps 2–4 are repeated for a number of cycles, with the imputations being updated at each cycle.

Multiple imputation

- Assumptions: Missing at Random.

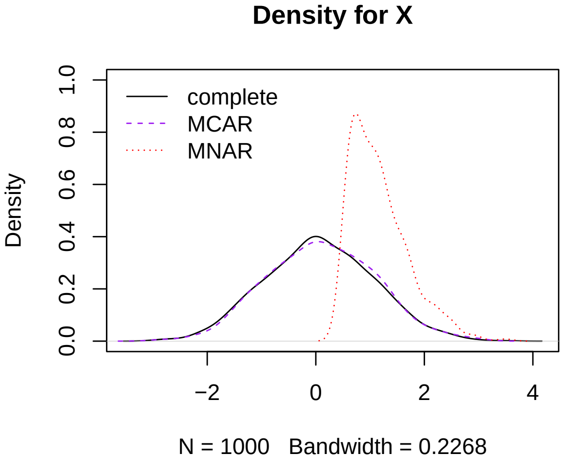
  We utilize other observed variables to impute.

- Usually produce different results with different starting point.

  One solution is to take average among the multiply imputed datasets.

How do we think of missing data?

- Missing **NOT** at random
    - Systematic selection leads to missing values.



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- Sensitive survey questions.
- Selective reporting by government / institution.
- Listwise deletion and multiple imputation cannot solve MNAR.

  Because we need more information about the systematic selection. These info are not in the observed variables.

Missing NOT at Random

- Transparency, Protest and Democratic Stability (Hollyer et al, BJPS, 2018)
- Measure transparency through missing data in country reports.
- Transparency is associated with a reduction in both the probability of democratic collapse and of the irregular removal of democratic leaders. Transparency stabilizes democratic rule.

Hollyer et al, 2018

- The availability of information on aggregate policy outcomes.
- Authors define transparency as a latent predictor of the reporting/non-reporting of data to the World Bank's World Development Indicators (WDI) data series.

Variable	Mean	Stand. Dev.	Min.	Max.
Transparency	2.50	2.19	−1.37	9.98
Growth (pct. GDP)	1.81	4.24	−26.2	31.9
GDP *per capita* (thousands 2005 PPP USD)	12.8	10.4	0.37	46.7
Ec. Openness (pct. GDP)	64.6	34.5	10.3	222
Parliamentary	0.42	0.49	0	1
Mixed System	0.18	0.38	0	1

Hollyer et al, 2018

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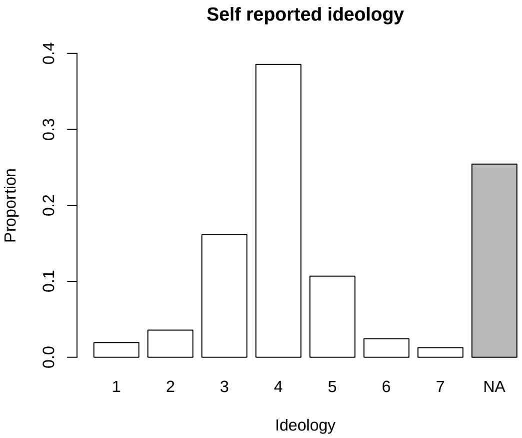
- Multiple impute the non-reported data?

  Assuming randomness in non-reporting, conditioning on GDP, Growth and political system.

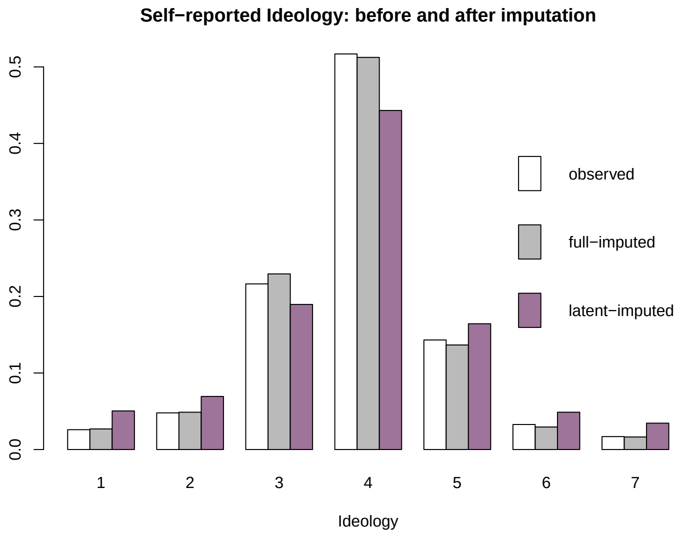
Liu, 2022



Self reported ideology
Proportion
0.0
0.1
0.2
0.3
0.4
1
2
3
4
5
6
7
NA
Ideology

Liu, 2022

Chinese respondents with extreme ideology are less likely to report.



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    $\rightsquigarrow$ listwise deletion
  - Missing at random $\rightsquigarrow$ multiple imputation
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    $\rightsquigarrow$ more careful modeling
- Dealing with missing values often leads to different study results!

How multiple imputation makes a difference? (Lall, 2017)

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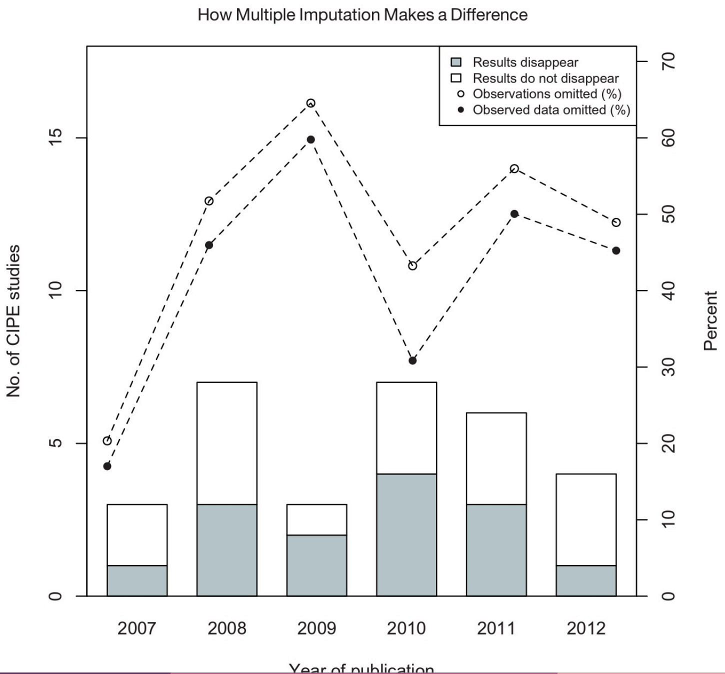
- Focuses on research in the major subfield of comparative and international political economy (CIPE).
- In almost half of the studies, key results “disappear” (by conventional statistical standards) when reanalyzed.


How Multiple Imputation Makes a Difference
Results disappear
Results do not disappear
Observations omitted (%)
Observed data omitted (%)
No. of CIPE studies
0
5
10
15
Percent
0
10
20
30
40
50
60
70
2007
2008
2009
2010
2011
2012
Year of publication