Measurement error and missing data

Killing two birds with one stone

Ruth Keogh

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On Behalf of TG4 Measurement Error and Misclassification

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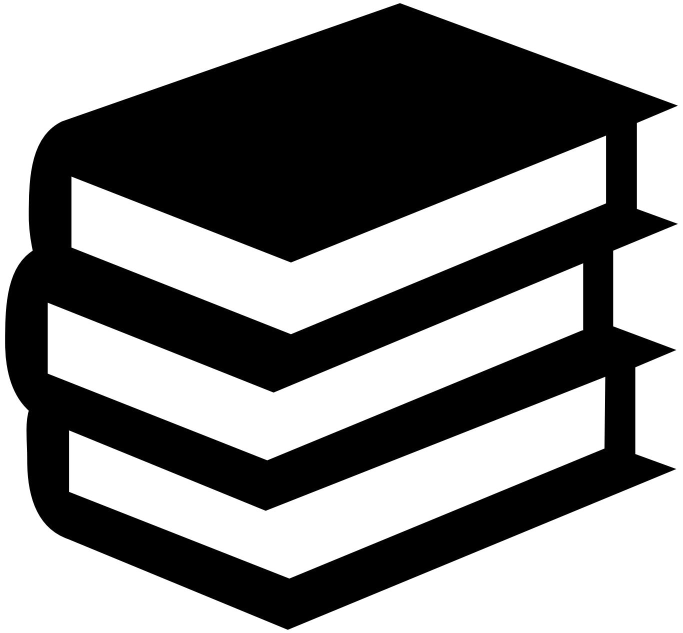
Measurement error and misclassification

Laurence Freedman
Victor Kipnis
Hendriek Bozhuizen
Raymond Carroll
Veronika Deffner
Kevin Dodd
Paul Gustafson
Ruth Keogh
Helmut Kuechenhoff
Pamela Shaw
Anne Thiebaut
Janet Tooze
Michael Wallace

Literature survey

What are people saying and doing about measurement error?



We surveyed the literature in four areas :

- Nutritional intake cohort studies
- Physical activity cohort studies
- Air pollution cohort studies
- Dietary intake distributions

Literature survey: N=81

What percentage of studies mentioned measurement error as a potential problem?

What percentage of studies used methods to mitigate the impact of measurement error?

What percentage of studies categorized their main exposure?

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80% (N=65)

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What percentage of studies used methods to mitigate the impact of measurement error?

6% (N=5)

What percentage of studies categorized their main exposure?

Literature survey: N=81

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What percentage of studies mentioned measurement error as a potential problem?	80% (N=65)
What percentage of studies used methods to mitigate the impact of measurement error?	6% (N=5)
What percentage of studies categorized their main exposure?	88% (N=71)

Literature survey: observations

- Most of those who mentioned error as a problem made an incomplete/incorrect claim
  - Many stated that their estimates could only be attenuated by measurement error
  - Some claimed no bias in associations but for spurious reasons

Literature survey: observations

- Most of those who mentioned error as a problem made an incomplete/incorrect claim
  - Many stated that their estimates could only be attenuated by measurement error
  - Some claimed no bias in associations but for spurious reasons

- Most studies categorized the continuous exposures
  - Common belief: categorization will reduce impact of measurement error
  - Categorizing can actually make things worse

References

Epidemiologic analyses with error-prone exposures: review of current practice and recommendations.

Shaw et al. *Annals of Epidemiology* 2018; 28: 821-828.

Measurement error is often neglected in medical literature: a systematic review.

Brackenhoff et al. *Journal of Clinical Epidemiology* 2018; 98: 89-97.

Five myths about measurement error in epidemiologic research.

van Smeden, Lash, Groenwold. DOI 10.17605/OSF.IO/MSX8D. https://osf.io/msx8d/

Forthcoming guidance papers

STRATOS guidance document on measurement error and misclassification of variables in observational epidemiology

Part 1 – basic theory and simple methods of adjustment

Ruth H Keogh, Pamela A Shaw, Paul Gustafson, Raymond J Carroll, Veronika Deffner, Kevin W Dodd, Helmut Küchenhoff, Janet A Tooze, Michael P Wallace, Victor Kipnis, Laurence S Freedman

Part 2 –more complex methods of adjustment and advanced topics

Pamela A Shaw, Paul Gustafson, Raymond J Carroll, Veronika Deffner, Kevin W Dodd, Ruth H Keogh, Victor Kipnis, Janet A Tooze, Michael P Wallace, Helmut Küchenhoff, Laurence S Freedman

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Jonathan Bartlett, University of Bath

Christen Gray, IQVIA

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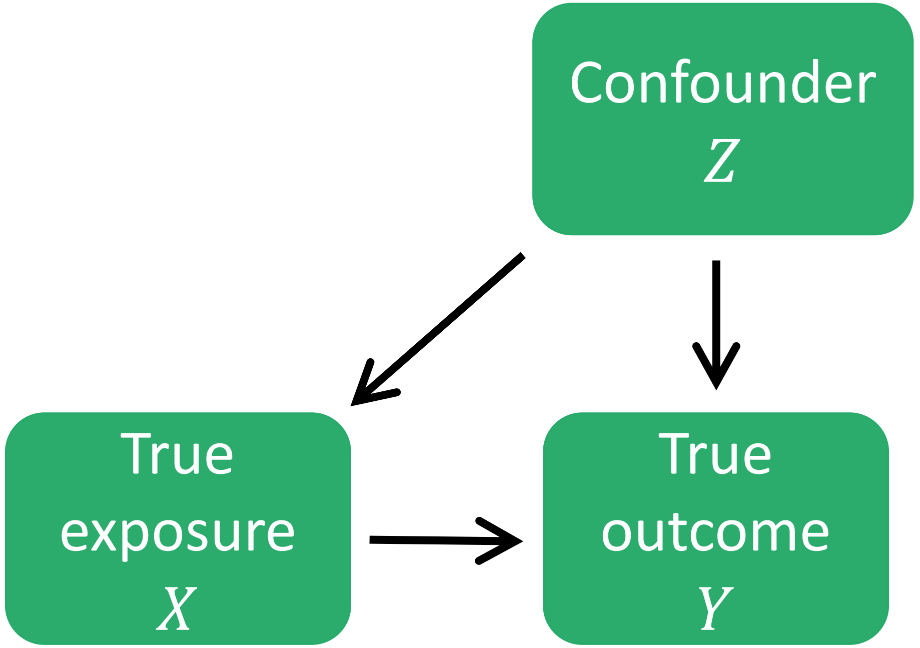
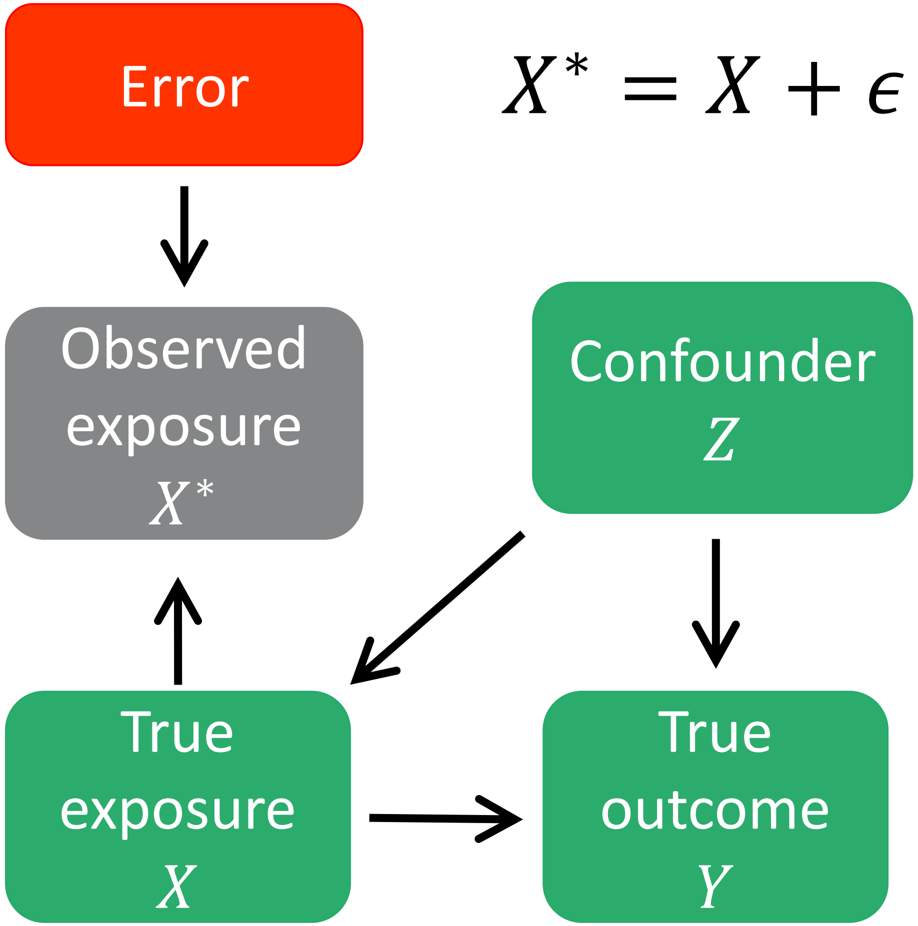
Notation and set-up

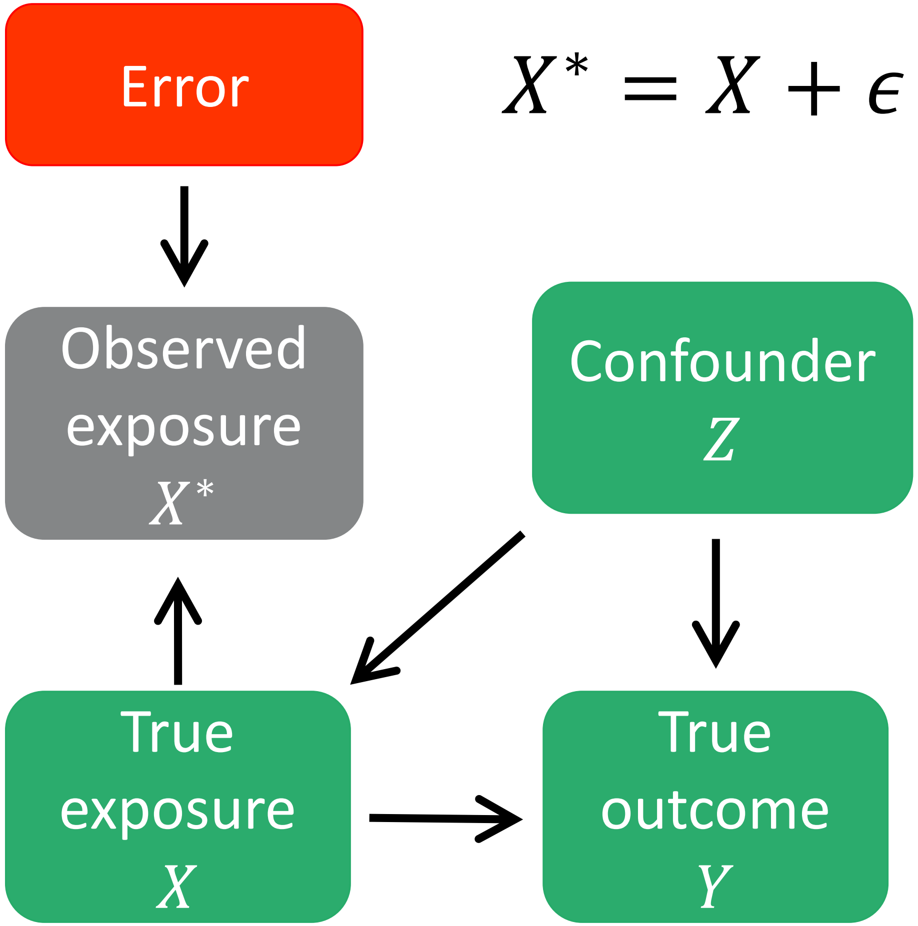


Notation and set-up



$$X^* = X + \epsilon$$

Notation and set-up

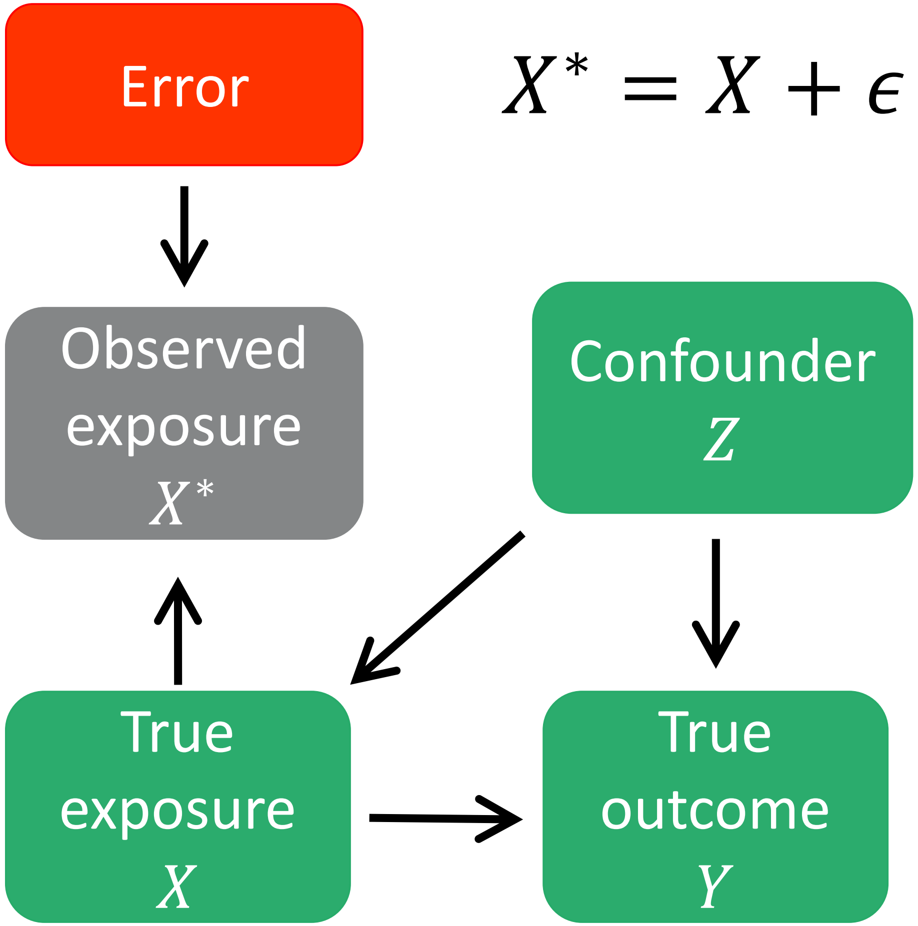


$$X^* = X + \epsilon$$

True outcome model: Using X

$$Y = \beta_0 + \beta_X X + \beta_Z Z + e$$

Notation and set-up



$$X^* = X + \epsilon$$

True outcome model: Using X

$$Y = \beta_0 + \beta_X X + \beta_Z Z + e$$

Naive outcome model: Using X^*

$$Y = \beta_0^* + \beta_X^* X^* + \beta_Z^* Z + e$$

Ancillary studies

To do something about the impact of measurement error in our analysis, we need to know the form and extent of the error

Validation study	Replicates study	Calibration study
X^*	X_1^*	X^*
X	X_2^*	X_1^{**}, X_2^{**}

Motivating example: NHANES data

- Association between systolic blood pressure (SBP) and deaths due to cardiovascular disease (CVD)
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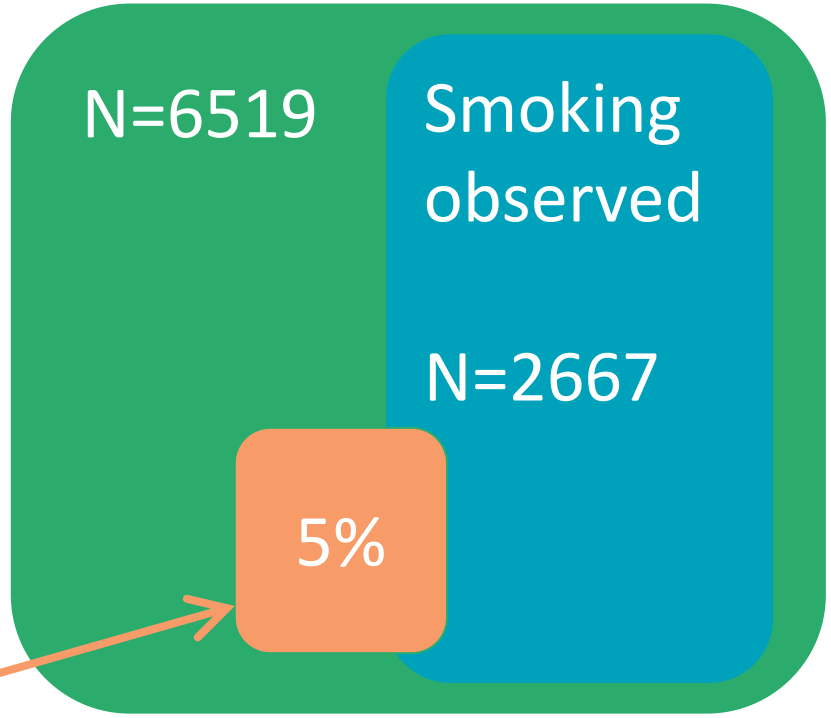

Replicate SBP measurement

Regression calibration

Obtain an estimate of $E(X|X^*, Z)$ using the ancillary study and use in the outcome regression model:

$$Y = \beta_0 + \beta_X E(X|X^*, Z) + \beta_Z Z + e$$

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Limitations

- Requires non-differential error assumption
- Requires an approximation for non-linear outcome models
- How do we accommodate missing data as well?

Multiple imputation (MI)

- Very popular method for handling missing data
- Measurement error can be viewed as a missing data problem – the ‘truth’ is missing

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…for some people

…for everyone!

Validation study

X^*

X

Replicates study

X_1^*

X_2^*

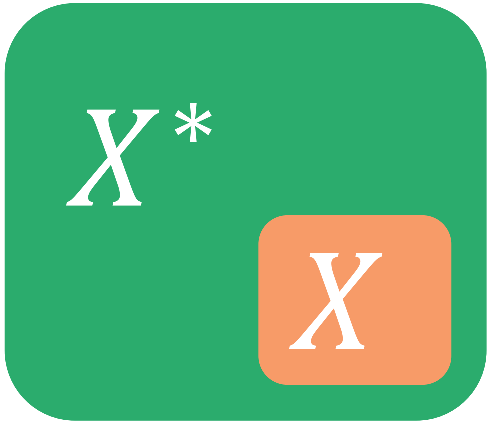
Calibration study

X^*

X_1^{**}, X_2^{**}

Multiple imputation (MI)

Validation study



Cole SR, Chu H and Greenland S. Multiple-imputation for measurement-error correction. Int J Epidemiol 2006; 35: 1074–1081.

1. For individuals with X missing, draw a value X from $X|X^*, Z, Y$
2. This gives a complete imputed data set
3. Fit the outcome model using the imputed data
4. Repeat for M imputed data sets
5. Pool the results using Rubin's Rules

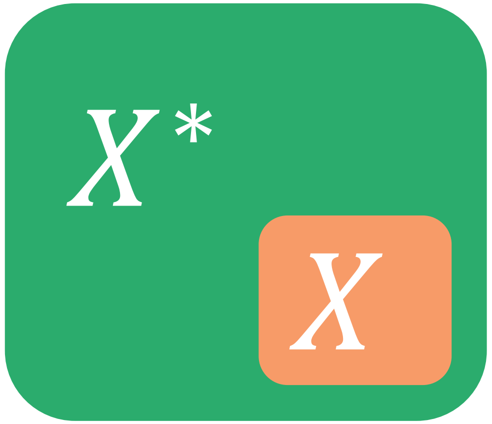
Multiple imputation (MI)

In the validation situation we benefit from the huge missing data literature on MI.

Carpenter & Kenward. Multiple imputation and its application. New York: Wiley. 2013

Sterne et al. Multiple imputation for missing data in epidemiological and clinical research: potential and pitfalls. BMJ 2009; 338: b2393

Validation study



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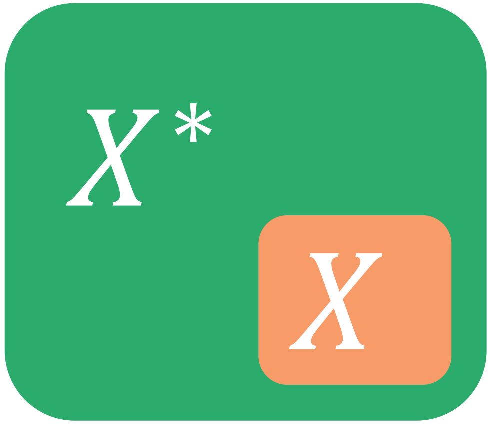


Software

R: mice, smcfcs
Stata: mi impute, smcfcs
SAS: PROC MI

Multiple imputation (MI)

Freedman et al. A comparison of regression calibration, moment reconstruction and imputation for adjusting for covariate measurement error in regression. Stat Med 2008; 27: 5195–5216.

Calibration study

X^*

X_1^{**}, X_2^{**}

Keogh & White. A toolkit for measurement error correction, with a focus on nutritional epidemiology. Stat Med 2014; 33: 2137-2155.

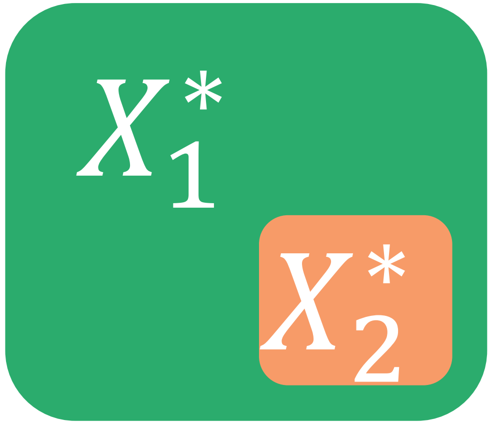
Replicates study

X_1^*

X_2^*

Multiple imputation (MI)

Replicates study



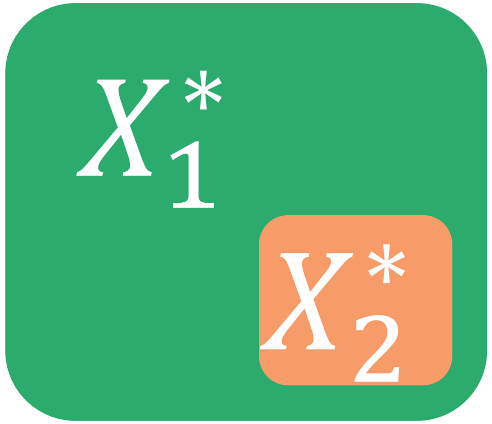
The difficult step of MI

1. For individuals with X missing, draw a value X from $X|X_1^*, X_2^*, Z, Y$

- We need to e.g. assume a multivariate normal distribution for $X, X_1^*, X_2^*|Z$
- This gives form of $p(X|X_1^*, X_2^*, Z, Y)$

Multiple imputation (MI)

Replicates study



The difficult step of MI

1. For individuals with X missing, draw a value X from $X|X_1^*, X_2^*, Z, Y$

- We need to assume a distribution for $X, X_1^*, X_2^*|Z$, e.g. multivariate normal
- This gives form of $p(X|X_1^*, X_2^*, Z, Y)$

- This approach is not very flexible
- There is no software and it is not very easy to implement

A more flexible MI approach

In general it is difficult to know what is the form of $X|X_1^*, X_2^*, Z, Y$

- There are non-linear terms in the model

$$Y = \beta_0 + \beta_X X + \beta_Z Z + \beta_{X2} X^2 + e$$

- The outcome model is not a linear regression

$$h(t|X, Z) = h_0(t) e^{\beta_0 + \beta_X X + \beta_Z Z}$$

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Meng. Multiple-imputation inferences with uncongenial sources of input. Statistical Science 1994; 9: 538-558.

Bartlett et al. Multiple imputation of covariates by fully conditional specification: Accommodating the substantive model. Stat Meth Med Res 2015; 24: 462-487.

A more flexible MI approach

Instead of trying to specify $X|X_1^*, X_2^*, Z, Y$,

…we specify $Y|X, Z$ and $X|Z$ and the measurement error model

Basic idea

1. Propose a potential imputed value for X from $X|X_1^*, X_2^*, Z$
2. Use a rejection sampling procedure to accept or reject the value as being from the target distribution $X|X_1^*, X_2^*, Z, Y$
3. The acceptance/rejection rule is a function of the outcome model

Substantive model compatible full conditional specification (SMCFCS)

A more flexible MI approach

Application for measurement error correction

- Validation study: we can use it directly
- Replicates: we extended the method to the setting of replicates

Keogh & Bartlett. Measurement error as a missing data problem. Handbook of Measurement Error and Variable Selection. 2019. Forthcoming.

Bartlett & Keogh. smcfcs: Multiple imputation of
covariates by substantive model compatible fully conditional specification. 2019.

https://github.com/ruthkeogh/meas_error_handbook

Motivating example: NHANES data

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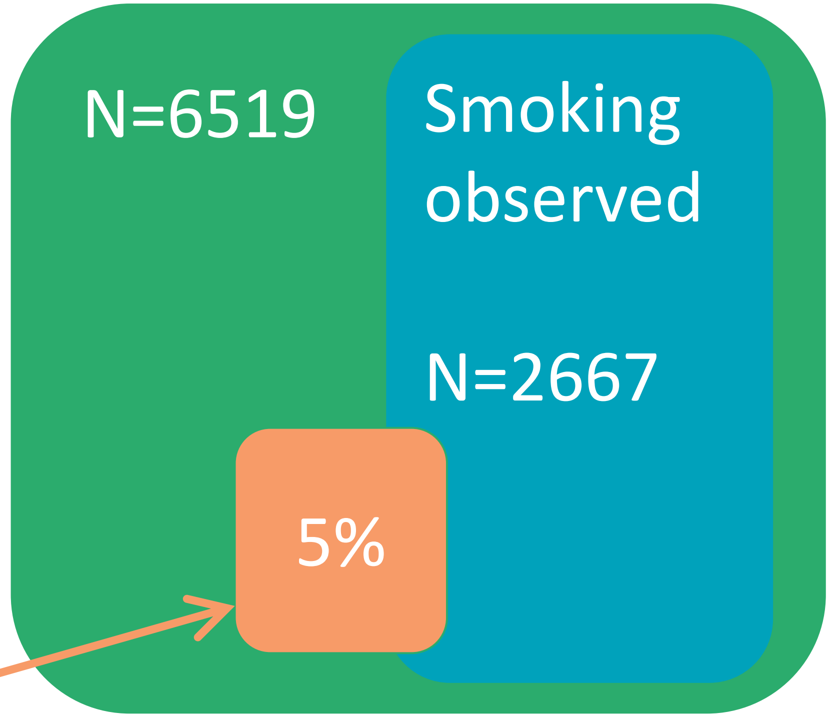

Replicate SBP measurement

Motivating example: NHANES data

First ignoring missing data…..

Covariate	Naïve analysis	Regression calibration	Multiple imputation
SBP	0.085 (0.014, 0.157)	0.114 (0.011, 0.222)	0.120 (0.020, 0.219)
Male	0.49 (0.30, 0.67)	0.49 (0.32, 0.68)	0.49 (0.30, 0.67)
Age	0.88 (0.77, 0.99)	0.87 (0.76, 0.99)	0.88 (0.77, 0.99)
Smoker	0.26 (0.07, 0.46)	0.26 (0.07, 0.45)	0.26 (0.07, 0.46)
Diabetes	0.50 (0.29, 0.72)	0.50 (0.28, 0.72)	0.50 (0.29, 0.72)

Motivating example: NHANES data

Accounting for missing data as well…

Covariate	Naïve analysis	Regression calibration	Multiple imputation	Multiple imputation 2
SBP	0.085 (0.014, 0.157)	0.114 (0.011, 0.222)	0.120 (0.020, 0.219)	0.104 (0.035, 0.173)
Male	0.49 (0.30, 0.67)	0.49 (0.32, 0.68)	0.49 (0.30, 0.67)	0.46 (0.35, 0.56)
Age	0.88 (0.77, 0.99)	0.87 (0.76, 0.99)	0.88 (0.77, 0.99)	1.04 (0.97, 1.11)
Smoker	0.26 (0.07, 0.46)	0.26 (0.07, 0.45)	0.26 (0.07, 0.46)	0.26 (0.09, 0.43)
Diabetes	0.50 (0.29, 0.72)	0.50 (0.28, 0.72)	0.50 (0.29, 0.72)	0.69 (0.56, 0.83)

N=2667

N=6519

Summary

- We commonly face more than one ‘data quality’ challenge at the same time
- Multiple imputation (and fully Bayesian approaches) enable us to ‘easily’ tackle measurement error and missing data together
- The smcfcs package in R facilitates this

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Bartlett & Keogh. Bayesian correction for covariate measurement error: A frequentist evaluation and comparison with regression calibration.
Stat Meth Med Res 2016; 27: 1695-1708.

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