

Strategies for handling missing data in randomised trials

MRC HTMR Clinical Trials Methodology Conference
Bristol, 5th October 2011
Session J: Missing Data

Ian White

MRC Biostatistics Unit, Cambridge, UK

Plan

1. Why do missing data matter?
 2. Popular analysis methods and their assumptions
 3. Which methods are best in a RCT?
 4. Intention-to-treat analysis strategy for randomised trials with missing outcomes
 5. Sensitivity analysis
- Work with: James Carpenter & Stuart Pocock (LSHTM), Nick Horton (USA), Simon Thompson (BSU)

Why do missing data matter?

1. **Loss of power** (cf. power with no missing data)
 - **can't** regain lost power
2. Any analysis must make an **untestable assumption** about the missing data
 - wrong assumption \Rightarrow **biased estimates**
3. Some popular analyses with missing data get **biased standard errors**
 - resulting in wrong p-values and confidence intervals
4. Some popular analyses with missing data are **inefficient**
 - confidence intervals wider than they need be

What to do: loss of power

Can't solve by analysis (but can exacerbate it!).

Approach by design:

- Minimise amount of missing data
 - Good communications with participants
 - Aim to follow everyone up
 - Make repeated attempts using different methods
- Reduce the impact of missing data
 - Collect reasons for missing data
 - Collect information predictive of missing values

What to do: analysis

A suitable method of analysis would:

- Make the correct assumption about the missing data
- Give an unbiased estimate (under that assumption)
- Give an unbiased standard error (so that P-values and confidence intervals are correct)
- Be efficient (make best use of the available data)

we can never be sure what is the correct assumption

→ **sensitivity analyses** are essential

US report: “The Prevention and Treatment of Missing Data in Clinical Trials”

- Commissioned by Food & Drug Administration
 - Written by a panel of top statisticians
 - National Research Council (2010)
1. Introduction and Background
 2. Trial Designs to Reduce the Frequency of Missing Data
 - focus on estimands (pre-trial)
 3. Trial Strategies to Reduce the Frequency of Missing Data
 4. Drawing Inferences from Incomplete Data
 - covers it all
 5. Principles and Methods of Sensitivity Analyses
 - lots of suggestions
 6. Conclusions and Recommendations

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Note: missing data are most commonly in the outcome, but may also occur in baseline covariates

How to approach the analysis

- Start by knowing:
 - extent of missing data
 - pattern of missing data (e.g. how many people with time 1 missing have time 2 observed?)
 - predictors of missing data and of outcome
- **Principled** approach to missing data:
 - identify a plausible assumption (with clinical colleagues)
 - choose an analysis method that's valid under that assumption
- Some analysis methods are **simple to describe** but have **complex** and/or **implausible assumptions**

The analysis toolkit

Simple methods

- Last observation carried forward (LOCF)
- Complete-case analysis
- Mean imputation
- Missing indicator method
- Regression imputation

More complex methods

- Multiple imputation
- Likelihood-based methods
- Inverse probability weighting (IPW)

Properties of analysis methods

| Method | For missing covariate | For missing outcome |
|-----------------------|-------------------------------------|---|
| LOCF | Not applicable | OK under LOCF ass ⁿ |
| Complete cases | Inefficient | Single Y: OK under MAR Repeated Y: inefficient |
| Mean imputation | OK in RCT | SE ↓↓↓ |
| Missing indicator | Fails to control confounding in epi | Not applicable |
| Regression imputation | OK under MAR (no Y in imp. model) | SE ↓↓ |
| Multiple imputation | OK under MAR | OK under MAR |
| Maximum likelihood | | |
| IPW | Inefficient or complex | OK under MAR Simple patterns only |

Missing at random (MAR)

- The probability that data are missing
 - may depend on the values of the observed data
 - does not depend on the values of the missing data (conditional on the values of the observed data)
- Example: blood pressure (BP) data are MAR if
 - older individuals are more likely to have their BP recorded (and age is observed and included in the analysis)
 - but at any age, individuals with low and high BP are equally likely to have their BP recorded

A comment on MAR

- A lot of statistical literature seems to regard MAR as the correct starting point for analyses with missing data
- I think the correct assumption depends on the clinical context
- A general argument in favour of MAR is that it tends to become more plausible as more variables are included in the model

A comment on LOCF

- Assumes last observation is **representative** of the missing value
 - i.e. **mean change after drop-out is zero**
- Can't verify this assumption from the data
 - not implied by **mean change in observed data is zero**
- Analysts rarely give a good justification, and instead justify LOCF (wrongly) on the grounds that
 - it is conservative: *not true in general*
 - it respects ITT by analysing all individuals
- Recall **principled** approach to missing data:
 - identify a plausible assumption
 - choose analysis that's valid under that assumption

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In this section I'm going to assume that MAR is a reasonably plausible assumption, or at least a good starting point, in a particular trial

Missing outcomes in a RCT under MAR:

1. single outcome

- Under MAR, cases with missing Y contribute no information
 - complete-cases analysis is correct!
- Regress outcome (Y) on randomised group (Z), adjusting for baseline covariates (X)
 - analysis of covariance, ANCOVA
 - this is the likelihood-based method
- Which X?
 - to make MAR valid, adjust for X that predict both outcome and missingness
 - to gain power, adjust for X that predict outcome
- But complications arise with composite outcomes or auxiliary information – see later

Missing outcomes in a RCT under MAR:

2. repeated outcome

Repeated quantitative outcome:

- Use a **mixed model** (likelihood-based)
- Include all observed outcome data
- Exclude any individuals with no post-baseline observations
- Include X's as before
- Software: Stata xtmixed, SAS proc mixed, R lme()
- There are some pitfalls
 - Don't allow a treatment effect at baseline
 - Allow a different treatment effect at each follow-up time
 - If possible, use unstructured variance-covariance matrix

Repeated binary outcome:

- May be worth using multiple imputation

What about multiple imputation?

- Idea of multiple imputation (tutorial: White et al, 2011)
 - Impute missing data m times from observed data
 - Analyse the m completed data sets
 - Combine estimates by Rubin's rules
- If imputation model = analysis model, MI is the same as fitting a [mixed] model to the observed data
 - but MI has additional random error
 - so why do MI?
- MI may be of value in a RCT
 - if auxiliary information (e.g. compliance or other trial outcomes) can be included in the imputation model
 - as a way to do sensitivity analyses
 - with composite outcomes
 - with repeated binary outcome

Missing baselines

Missing baselines in RCTs are a completely different problem from missing outcomes

- Not a source of bias: baseline adjustment is used to gain precision
- Complete cases analysis is a very bad idea
- Almost anything else is OK (White & Thompson, 2005)
 - in particular, **mean imputation or missing indicator method are OK**
 - provided randomisation is respected
- **The above is only true when estimating the effect of a randomised intervention on outcome**

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Intention-to-treat (ITT) principle

- Include everyone randomised ...
- ... in the group to which they were assigned (whether or not they completed the intervention)

What does ITT mean with missing outcome data?

- “The statistical analysis of a clinical trial generally requires the **imputation** of values to those data that have not been recorded” (CPMP, 2001)
- “Although those participants [who drop out] cannot be included in the analysis, it is customary still to refer to **analysis of all available participants** as an intention-to-treat analysis” (Altman et al, 2001)
- “Full set analysis generally requires the **imputation of values or modelling** for the unrecorded data” (Eur. Medicines Agency, 2010)
- “We replaced mention of ‘**intention to treat**’ analysis, a widely **misused term**, by a more explicit request for information about retaining participants in their original assigned groups” (CONSORT, 2010)

Difficulties with ITT

- Including all randomised individuals in the analysis isn't enough to make an analysis valid
- The desire to include all randomised individuals in the analysis
 - reduces emphasis on the appropriate assumptions
 - leads to uncritical use of simple imputation methods, esp. Last Observation Carried Forward (LOCF)
 - leads to unnecessary use of complex methods, esp. multiple imputation
 - biases against MAR-based analyses

Strategy for intention to treat analysis with incomplete observations

(White et al, BMJ, 2011)

1. Attempt to **follow up** all randomised participants, even if they withdraw from allocated treatment
2. Perform a main analysis of all observed data that is valid under a **plausible assumption** about the missing data
3. Perform **sensitivity analyses** to explore the effect of departures from the assumption made in the main analysis
4. **Account for all randomised participants, at least in the sensitivity analyses**

Example: QUATRO trial

- European multicentre RCT to evaluate the effectiveness of adherence therapy in improving quality of life for people with schizophrenia (Gray *et al*, 2006)
- Primary outcome: quality of life measured by the SF-36 MCS scale at baseline and 52-week follow up

| | Intervention | Control |
|---------------------------|--------------|---------|
| Total n | 204 | 205 |
| Missing outcome | 14% | 6% |
| Mean of observed outcomes | 40.2 | 41.3 |
| SD of observed outcomes | 12.0 | 11.5 |

QUATRO trial: ITT analysis strategy

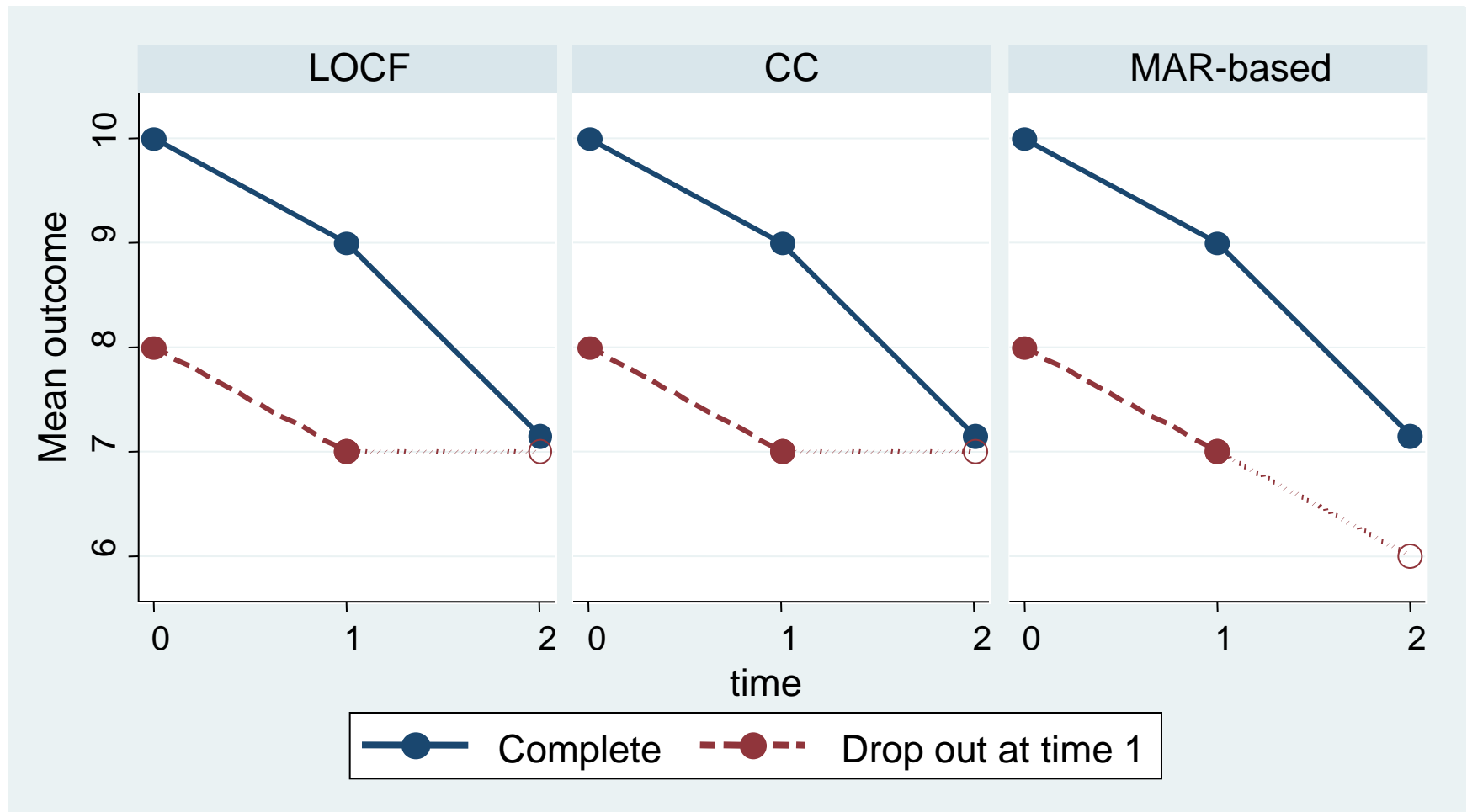
1. We did attempt to **follow up** all randomised individuals
2. **Main assumption:** no difference between missing and observed values, once adjusted for baseline variables (MAR)
Main analysis: analysis of covariance on complete cases
 - intervention effect = -0.33 (s.e. 1.11)
3. **Sensitivity analysis:** consider possible differences between missing and observed values, allowed to be different in each arm
 - coming next
4. All randomised individuals were included in the sensitivity analyses

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How to do sensitivity analyses?

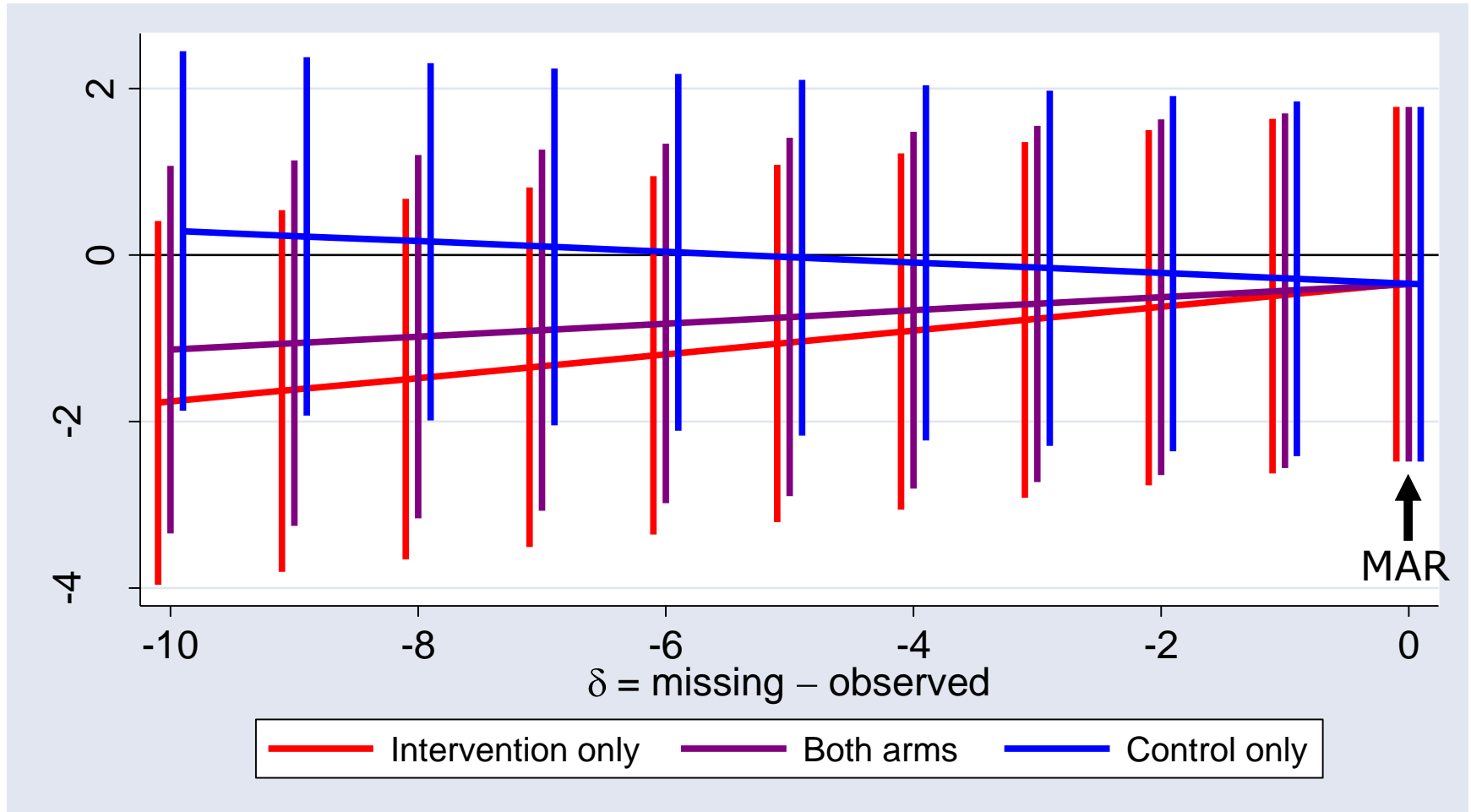
- *Not* LOCF for main analysis, CC for sensitivity analysis



How to do sensitivity analyses?

- *Not* LOCF for main analysis, CC for sensitivity analysis
- Instead, specify the numerical value of “sensitivity parameter(s)” governing the degree of departure from the main assumption (Kenward *et al*, 2001)
 - e.g. the degree of departure from MAR
 - “Principled sensitivity analysis”
- My approach:
 - let $\delta = \{\text{mean of missing data}\} - \{\text{mean of observed data}\}$ so $\delta = 0$ is MAR
 - get plausible range of δ from subject matter
 - vary δ in both arms
 - vary δ in one arm ($\delta=0$ in other arm)
- Methods: White *et al* (2007) or `rctmiss` software

Example: QUATRO data



Conclusions & discussion

- Missing baselines: use simple methods that respect randomisation
- Missing outcomes: focus on assumptions, not methods
- ANCOVA and mixed models are often the best strategy for missing outcomes in RCTs
 - use MI with auxiliary data (e.g. compliance) or possibly as a way to do sensitivity analyses
- An intention-to-treat analysis strategy should include all individuals in sensitivity analyses
 - but not necessarily in main analyses
- Sensitivity analyses can be done in various ways
 - install my software `rctmiss` in Stata using `net from` http://www.mrc-bsu.cam.ac.uk/IW_Stata/missing

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