# Systematic handling of missing data in complex study designs – Experiences from the Health 2000 and 2011 Surveys

### Tommi Härkänen<sup>1</sup> J Karvanen H Tolonen R Lehtonen K Djerf T Juntunen S Koskinen

Institute for Health and Welfare / Department of Health

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<sup>1</sup>E-mail: Tommi.Harkanen@thl.fi

Härkänen, Karvanen et al. (THL / TERO)

Missing data in complex study designs



Application of graphical models

2 The Health 2000 and 2011 Surveys

3 Correcting effects of missing data



Härkänen, Karvanen *et al.* (THL / TERO)

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How to communicate assumptions of steps above to other researchers?



A graphical model

Causal node X Variables of scientific interest in the population, possibly unobserved.





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Causal node X Variables of scientific interest in the population, possibly unobserved. Selection node  $\mathfrak{R}$  has the possible values 1 selected and 0 not selected. Common nodes are sampling r corresponding to sampling design and participation R of the sample members.

Selection node

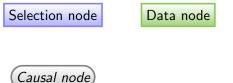




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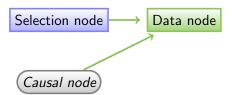


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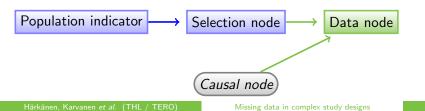




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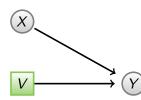
Population indicator  $r_{\Omega} \equiv 1$ .





Different probabilities:

Distribution of outcome Causal model  $\mathbb{P}$ {Y | V, X}.



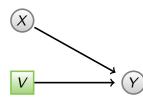


TERO) Missing data in complex study designs

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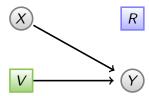


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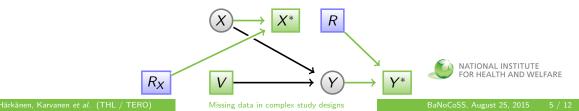
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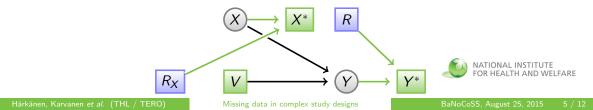
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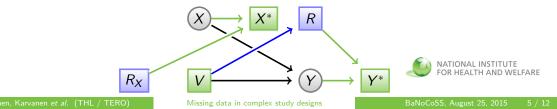
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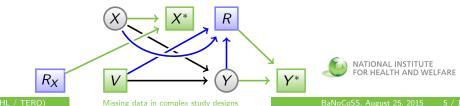
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- Not missing at random (NMAR)  $\Rightarrow$

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New sample of 1,994 young adults (aged 18 to 28)



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- Oldest age groups: Illnesses, disabilities, weak functional capacity
- Young age groups: Male



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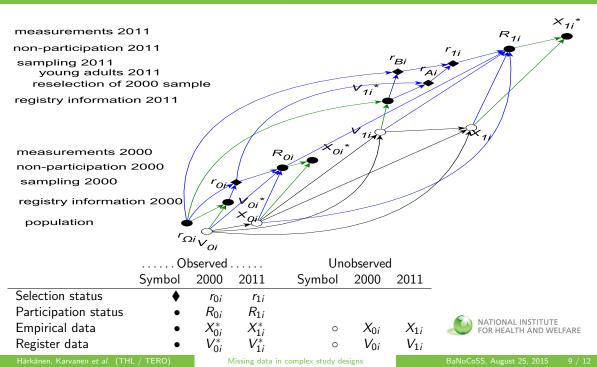
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### Inverse probability weights (IPW)

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Participants of Health 2000 Register data and observed Health 2000 Survey data were used. Weighting model was selected using the Bayesian Information Criterion: self-reported health and work ability, and participation frequency in clubs or associations.



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#### Multiple imputation

Imputation model 1 (MI1) contained categorical age, gender, language and education Imputation model 3 (MI3) In addition to MI1 and IPW, also body mass index (BMI), systolic blood pressure and smoking measured in 2000.

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# Results in the Health 2011 Survey

Variable	Clustering	Missing data method	Prev. (%)	SE
Disability pension	SRS	Complete case analysis	8.8	0.4
	Complex	IPW weights	9.3	0.4
	Complex	Doubly Robust	9.3	0.5
	Complex	MI1	9.4	0.5
	Complex	MI3	9.5	0.4
	Complex	Full sample prevalence	9.5	0.4
Hospitalization	SRS	Complete case analysis	16.6	0.5
	Complex	IPW weights	16.9	0.5
	Complex	Doubly Robust	17.2	0.6
	Complex	MI1	17.4	0.9
	Complex	MI3	17.2	0.5
	Complex	Full sample prevalence	17.6	0.5
Medication	SRS	Complete case analysis	40.2	0.7
	Complex	IPW weights	40.8	0.8
	Complex	Doubly Robust	41.4	0.7
	Complex	MI1	41.0	0.9
	Complex	MI3	41.8	0.7
	Complex	Full sample prevalence	41.9	0.6



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### Statistical methods to handle missing data

Our empirical analyses suggest that the multiple imputation methods managed to remove most bias caused by the non-response.

