

Compensating for Non-response in Biosocial Research:

Simulation Study from a Cross-sectional Analysis

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Biomarkers in Longitudinal Studies in the UK

- Understanding Society
- Millennium Cohort Study
- British Cohort Study
- Child Development Study
- English Longitudinal Study of Ageing

English Longitudinal Study of Ageing (ELSA)

- Data from 11,391 core sample members of men and women over 50 years living in private households
- Multistage stratified probability sample from the Health Survey of England (HSE) with refreshment samples
- Further health examinations including blood samples (W2, W4 & W6) and hair samples (W6)

Missing Information in ELSA

- Potential non-response at three different stages:
 - Main interview (CAPI)
 - Health examination (Nurse visit)
 - Blood/Hair sample collection

Patterns of Missing information

- Missing completely at random (MCAR)
- Missing at random (MAR)
- Missing not at random (MNAR)

Patterns of Missing information

- Missing completely at random

X



Y

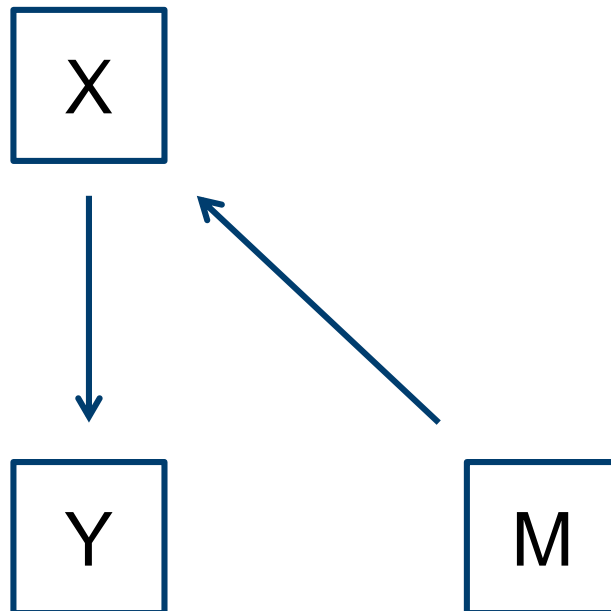
M

X explanatory variable
Y depend variable

M missingness of Y

Patterns of Missing information

- Missing at random

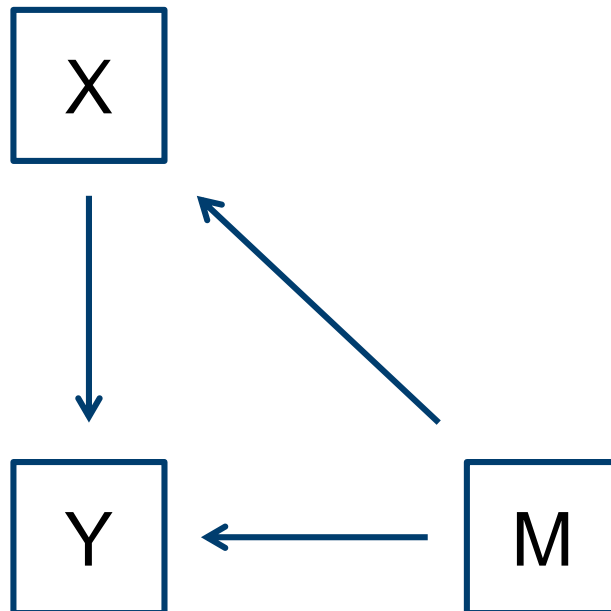


X explanatory variable
Y depend variable

M missingness of Y

Patterns of Missing information

- Missing not at random



X explanatory variable
Y depend variable

M missingness of Y

Accounting for missing data bias

- Several methods for missing data compensation
- Confusion over effectiveness of methods
- Problem of missing data is ignored
(assumption of MAR)

Objective

- Test and evaluate several analytical approaches
- Simulation study based on data from ELSA (wave 2)
- Comparison of five different approaches
- Evaluation over all three missingness patterns

Strategy

Step 1

Choose substantive model

Step 2

Select data in ELSA, expand sample size

Step 3

Run baseline model on “true” values

Step 4

Create missing data for MCAR, MAR and MNAR

Step 5

Test five different compensation approaches

Step 6

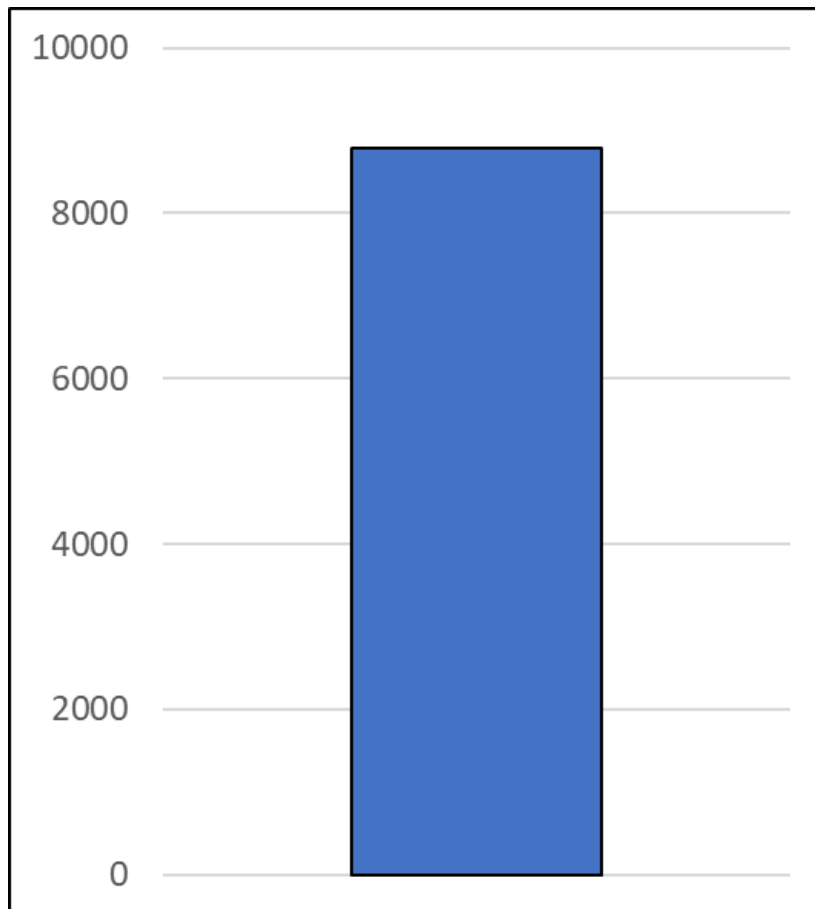
Compare with “true” model and evaluate effectiveness

Step 1 – Substantive model

Impact of socio-economic status on biomarker level

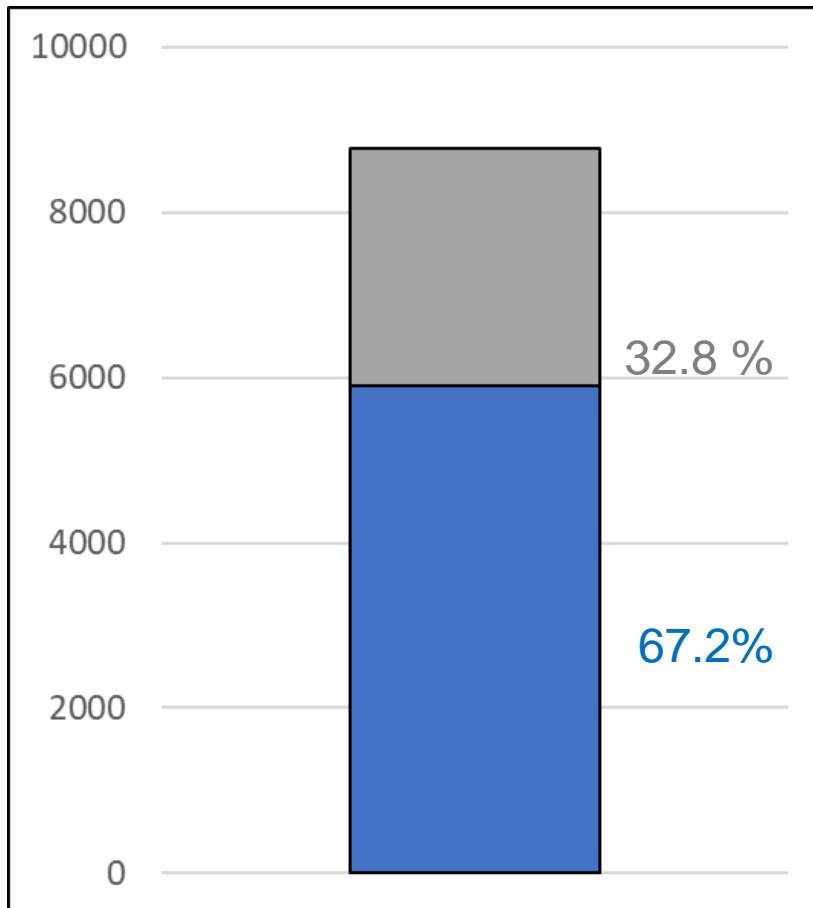
- SES
 - Education, occupational class and wealth quintile
- Biomarker
 - C-reactive protein (CRP)
- Confounding variables
 - Age, sex, physical activity, BMI, Longstanding illness, pain, general health, BP, in paid work

Step 2 – ELSA missing information



8.780
Wave 2 core member

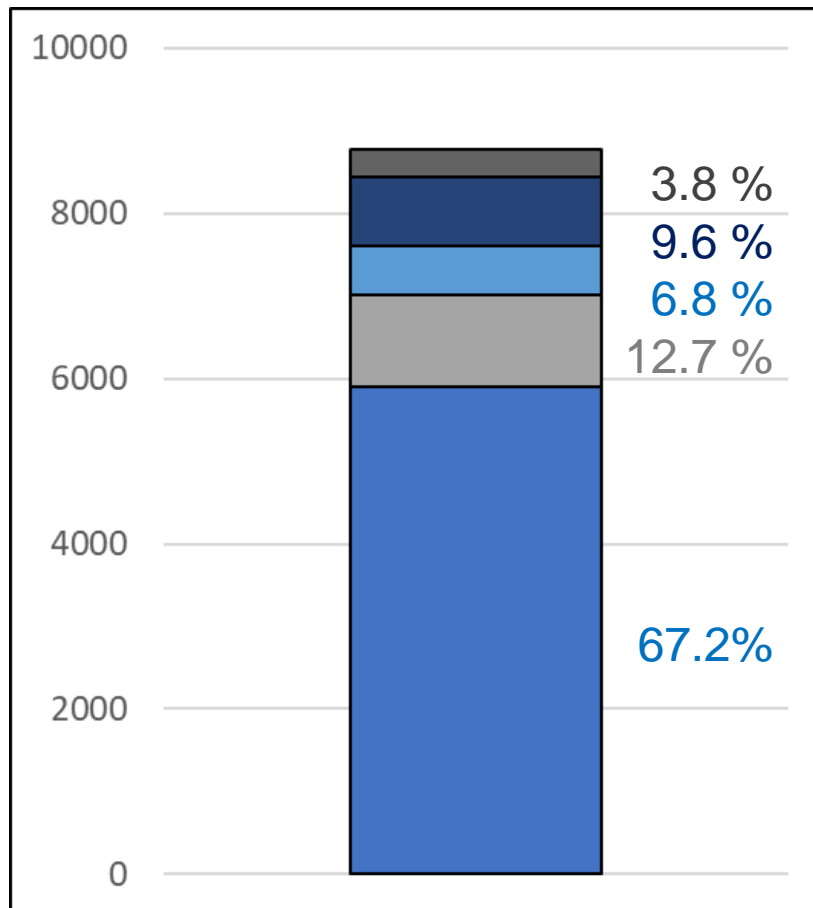
Step 2 – ELSA missing information



2.881
Non-response and missing

5.899 Eligible blood samples

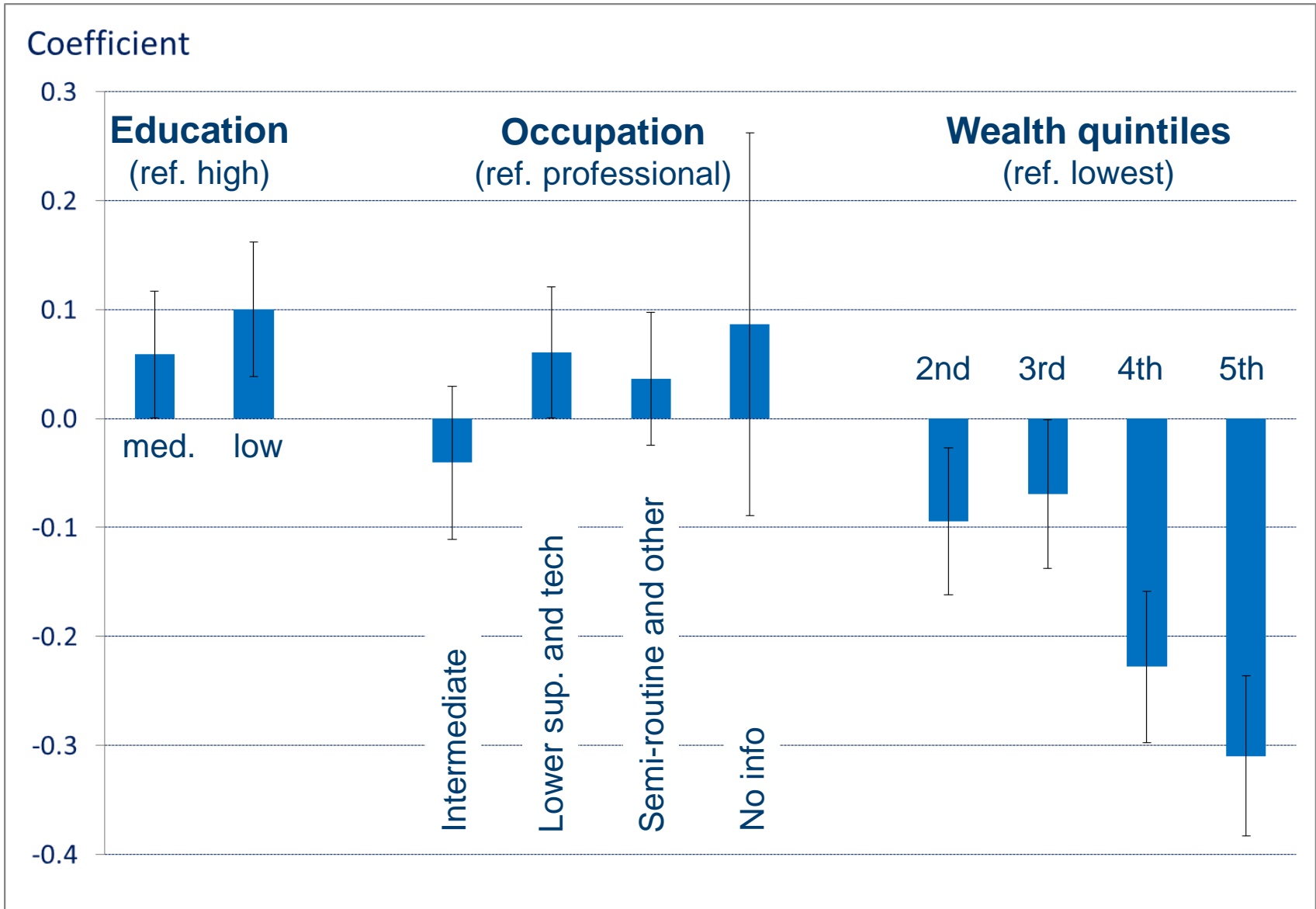
Step 2 – ELSA missing information



- 332 Unusable blood sample
- 839 No blood sample
- 596 Refuse blood sample
- 1.114 Refuse of nurse visit
- 5.899 Eligible blood samples

Step 3 – Model on expanded full dataset

- Logistic regression on logged CRP values
(10.000 sample)
- Coefficients for all three SES variables as baseline for simulation study



Step 4 – Creating missing data patterns

- **MCAR:** Missingness is completely random
- **MAR:** Missingness dependent on age, sex, wealth and health
- **MNAR:** Missingness dependent also on level of CRP
- 100 simulation datasets for each missing patterns

Step 5 – Five compensation methods

- Complete Case (CC)
- Inverse Propensity Weighting (IPW)
- Selection model using Mills Ratio (MR)
- Multiple Imputation (MI)
- Multiple Imputation with Mills Ratio (MI+MR)

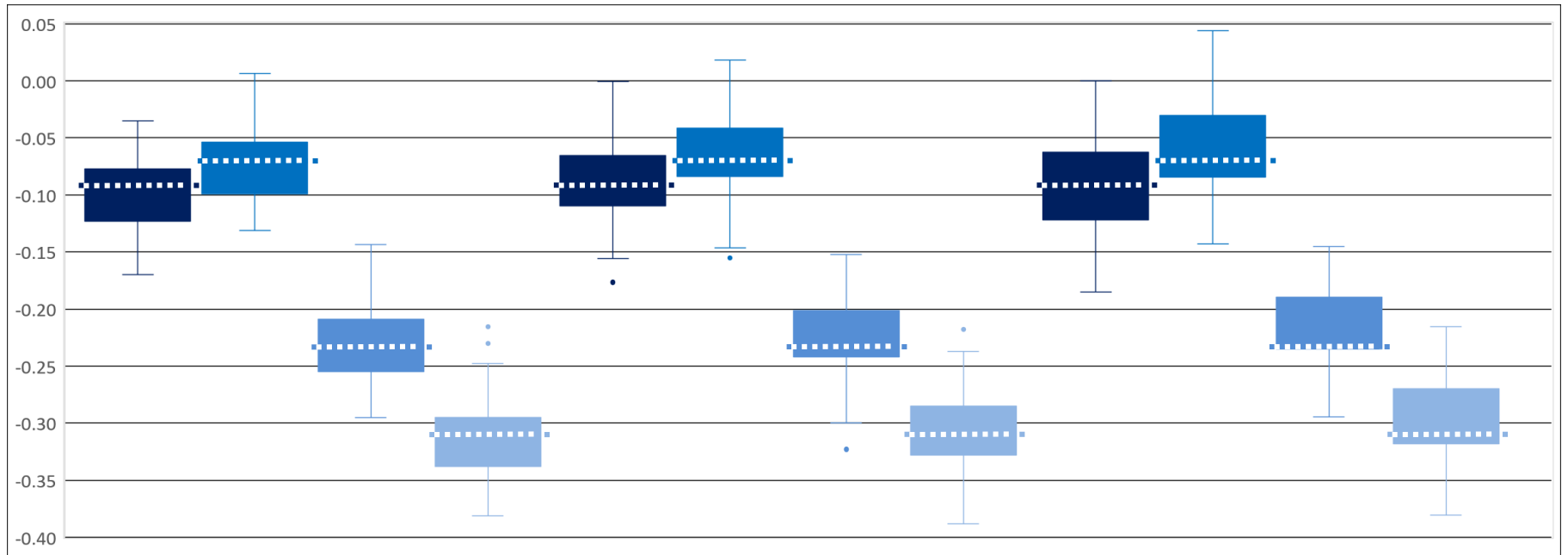
Step 6 – Run and evaluate simulations

	CC	IPW	MR	MI	MI+MR
MCAR					
MAR					
MNAR					

Expectation

	CC	IPW	MR	MI	MI+MR
MCAR	Green	White	White	Red	Red
MAR	Red	Green	White	Green	White
MNAR	Red	White	Green	White	Green

Complete Case – Wealth Quintiles



MCAR

MAR

MNAR

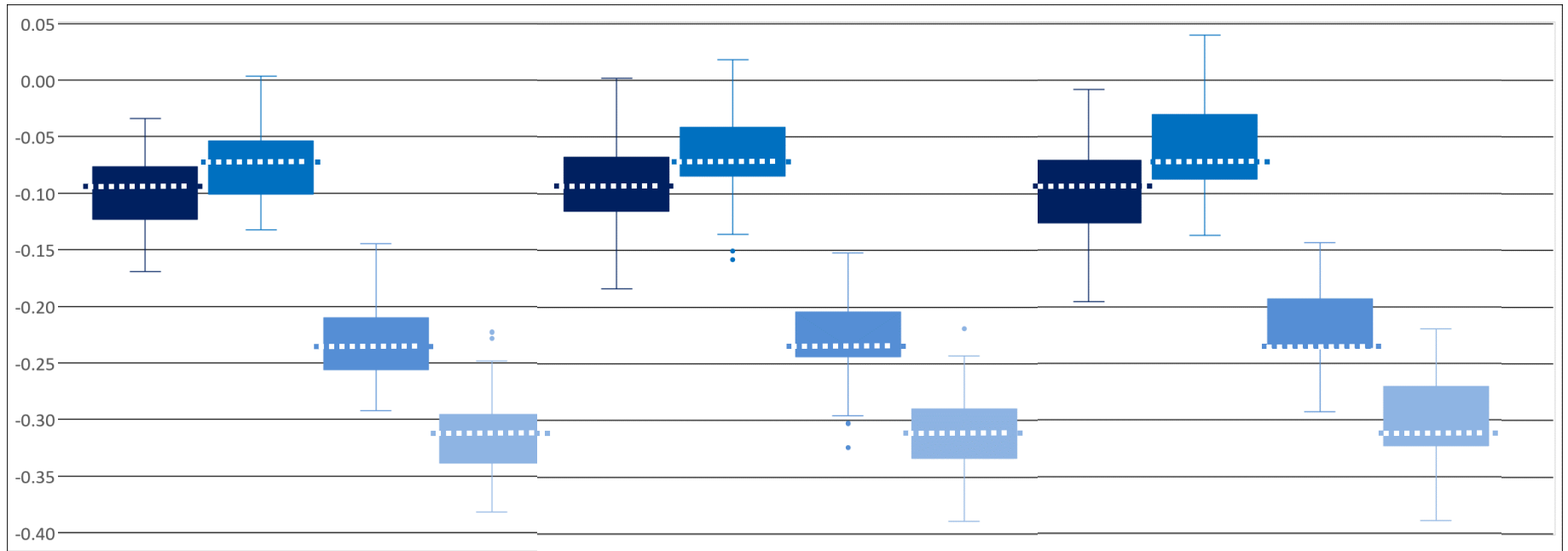
 2nd quintile (-0.09)

 4th quintile (-0.23)

 3rd quintile (-0.07)

 highest quintile (-0.31)

IPW – Wealth Quintiles



MCAR

MAR

MNAR

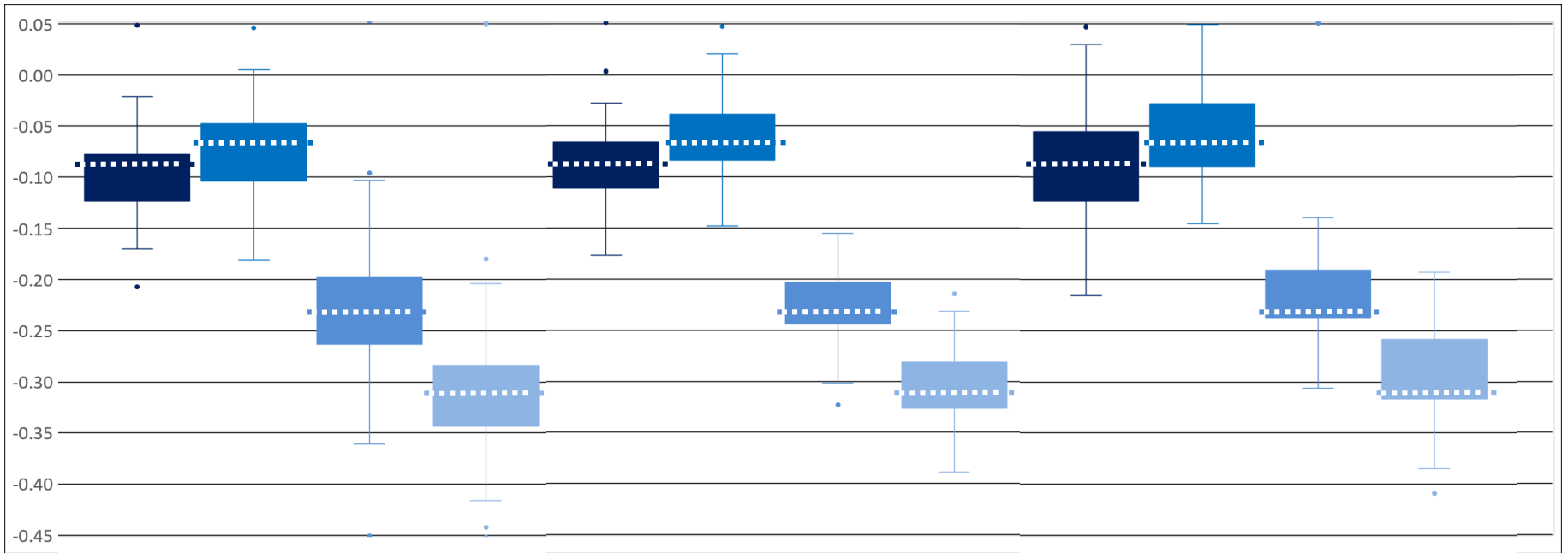
 2nd quintile (-0.09)

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 3rd quintile (-0.07)

 highest quintile (-0.31)

MR – Wealth Quintiles



MCAR

MAR

MNAR

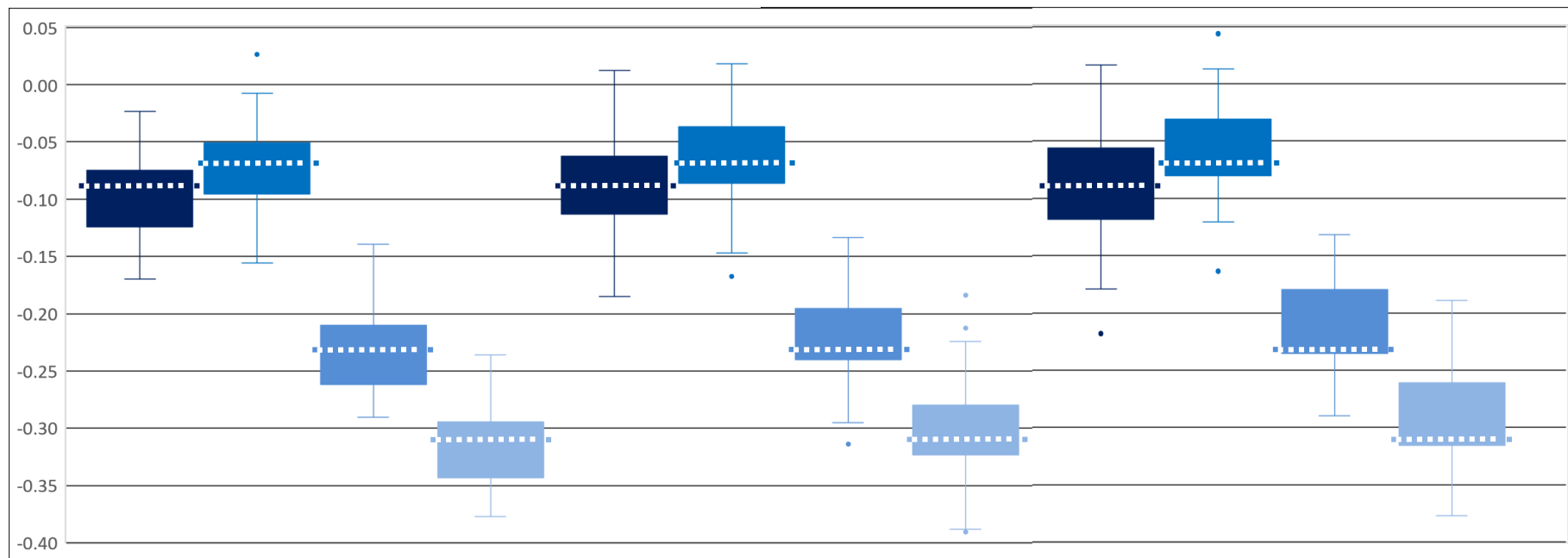
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 3rd quintile (-0.07)

 highest quintile (-0.31)

MI – Wealth Quintiles



MCAR

MAR

MNAR

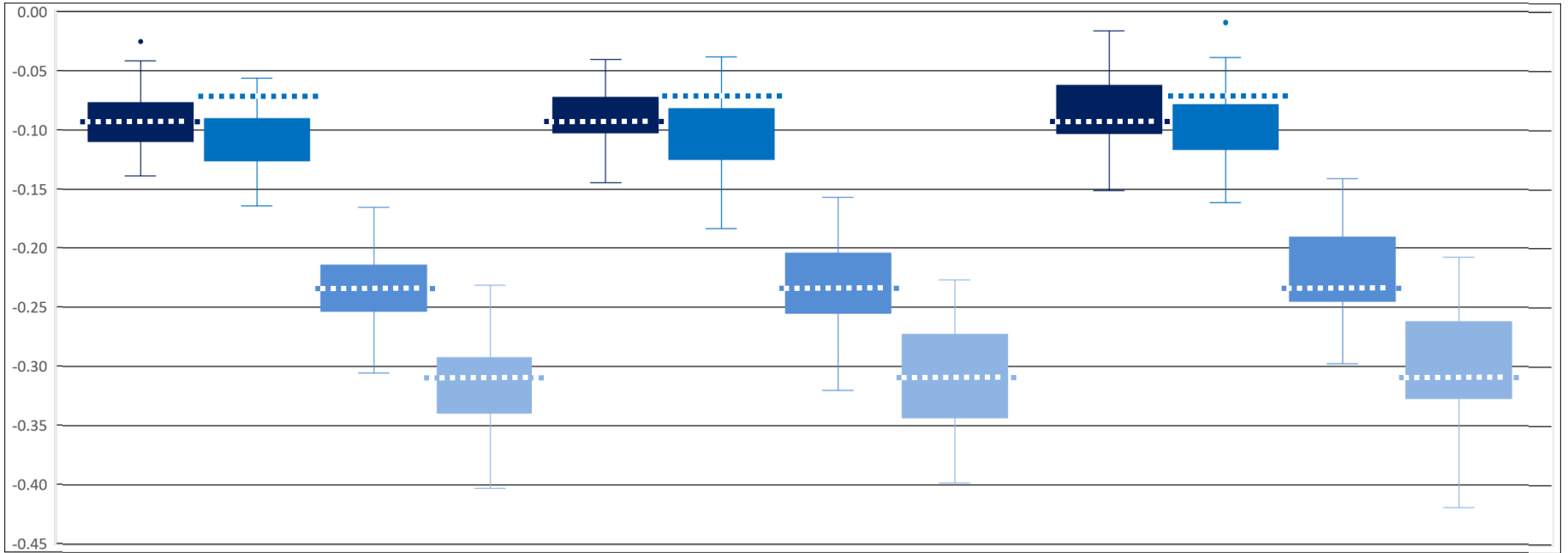
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highest quintile (-0.31)

MI+MR – Wealth Quintiles



MCAR

MAR

MNAR

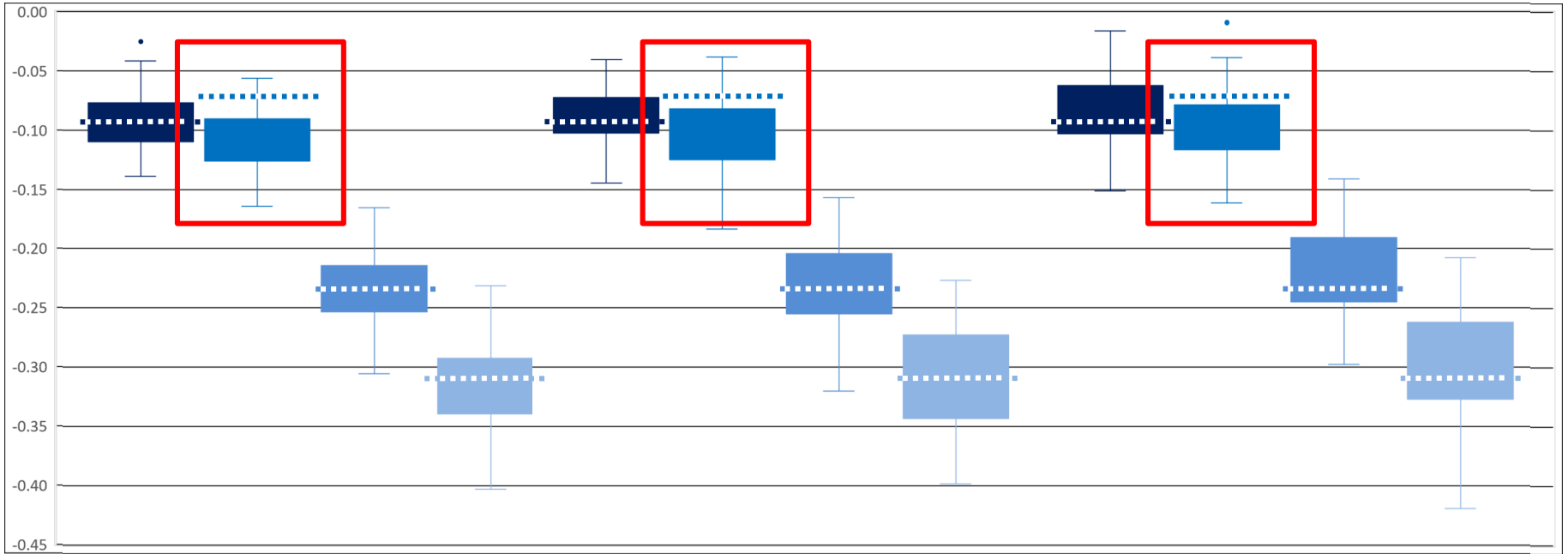
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MI+MR – Wealth Quintiles



MCAR

MAR

MNAR

 2nd quintile (-0.09)

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 highest quintile (-0.31)

Expectation

	CC	IPW	MR	MI	MI+MR
MCAR	Green	White	White	Red	Red
MAR	Red	Green	White	Green	White
MNAR	Red	White	Green	White	Green

Observation

	CC	IPW	MR	MI	MI+MR
MCAR	Green	White	White	White	Red
MAR	White	Green	White	Green	Red
MNAR	White	White	Green	White	Red

Conclusions

- No clear patterns
- Multiple Imputation and Mills Ratio method has no advantage
- MCAR and MAR rather robust
- MNAR bias not compensated with these methods

Future Research

- Expand the simulation study to larger iteration number
- Simplify substantial model
- Test and evaluate effectiveness of methods depending on the proportion of missingness in dataset
- Longitudinal analysis including wave 4 and wave 6 using growth curve modelling

Thank you for your attention

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