

Synthesizing Contextual Effects: A Comparison of the Two-Stage Meta-Analytic and One-Stage Multilevel Modeling Approaches in the presence of Individual Participant Data

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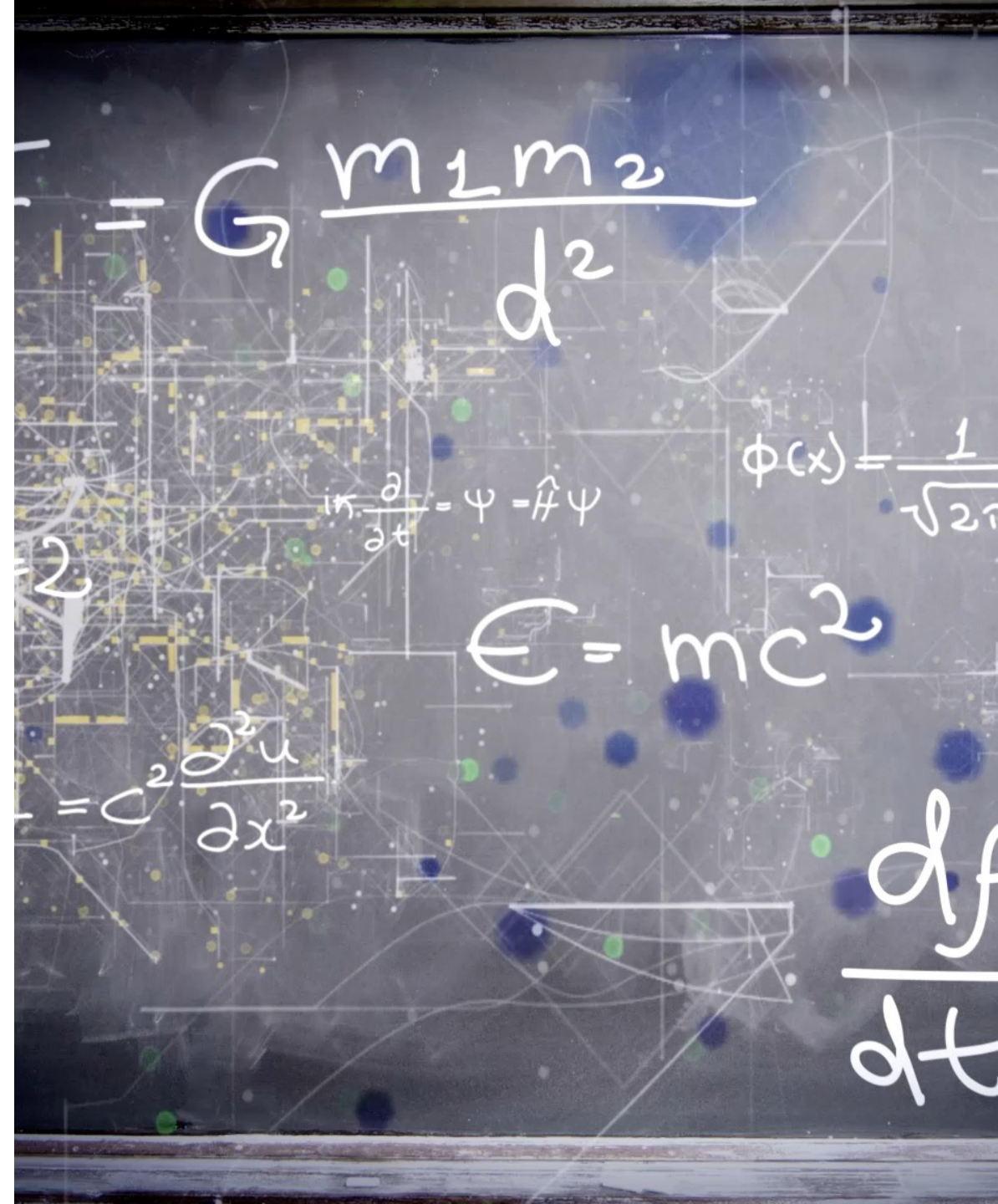
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Introduction

Group Composition Effects

Contextual effects: evaluate whether group-level characteristics contribute to outcomes beyond what can be explained by individual-level characteristics.

- Socioeconomic status
- School climate
- Big-Fish-Little-Pond-Effect

The models that include the same variable at both individual and group levels

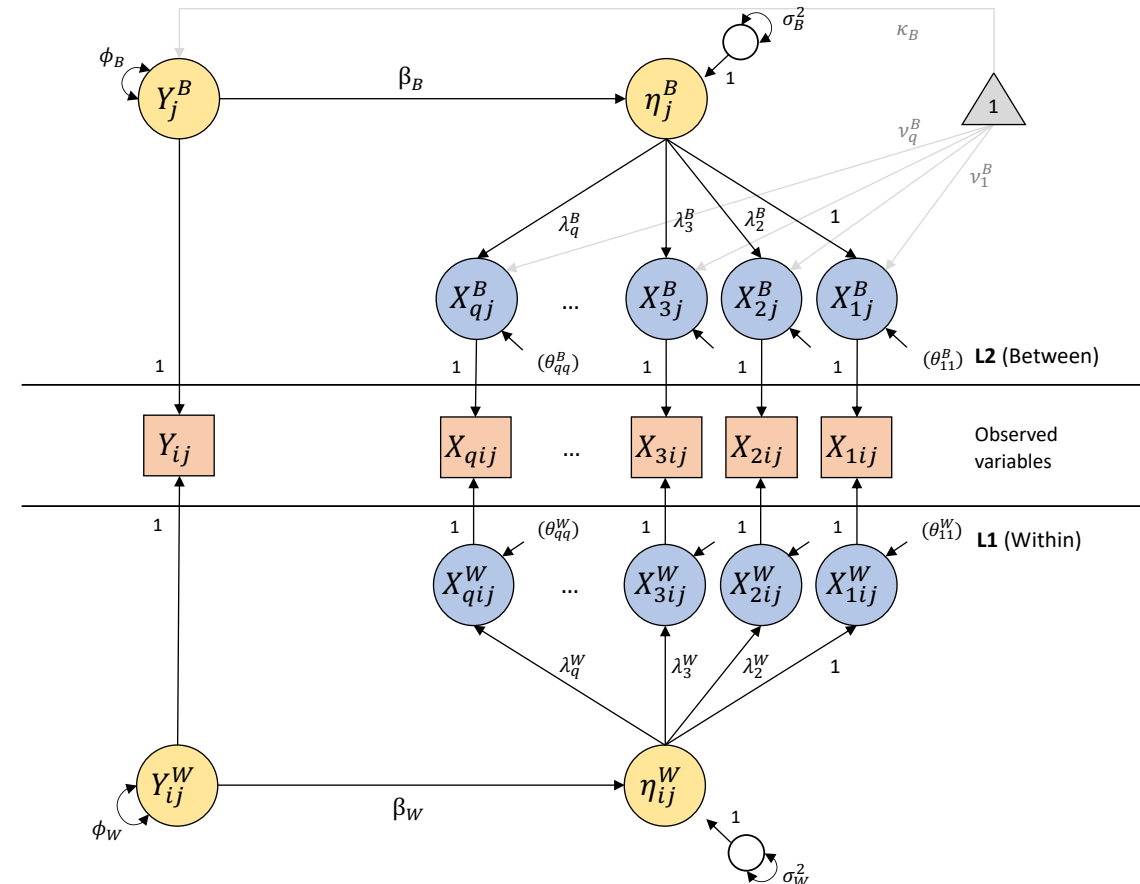
Introduction

Group Composition Effects

Manifest Approach

- Group compositions are often uncertain and must be inferred from the scores of individuals in the sample.
- Measurement error
- Sampling error
- Decomposing within and between effects

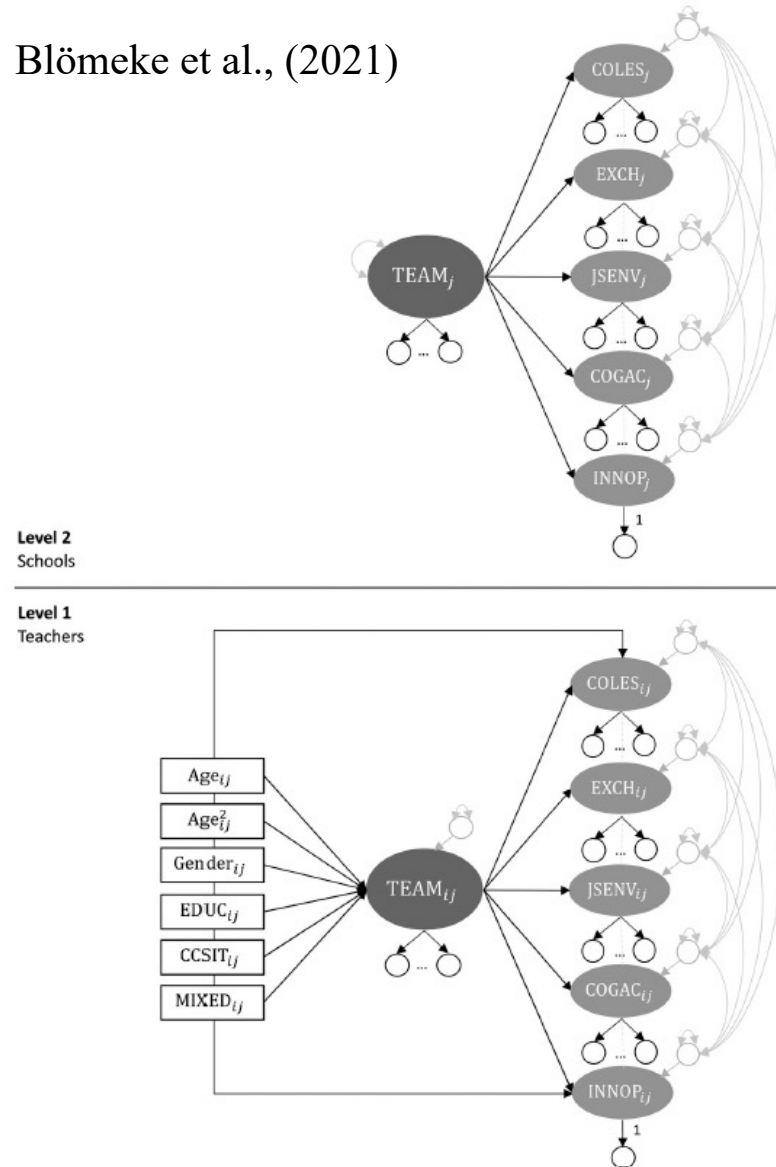
Latent Approach



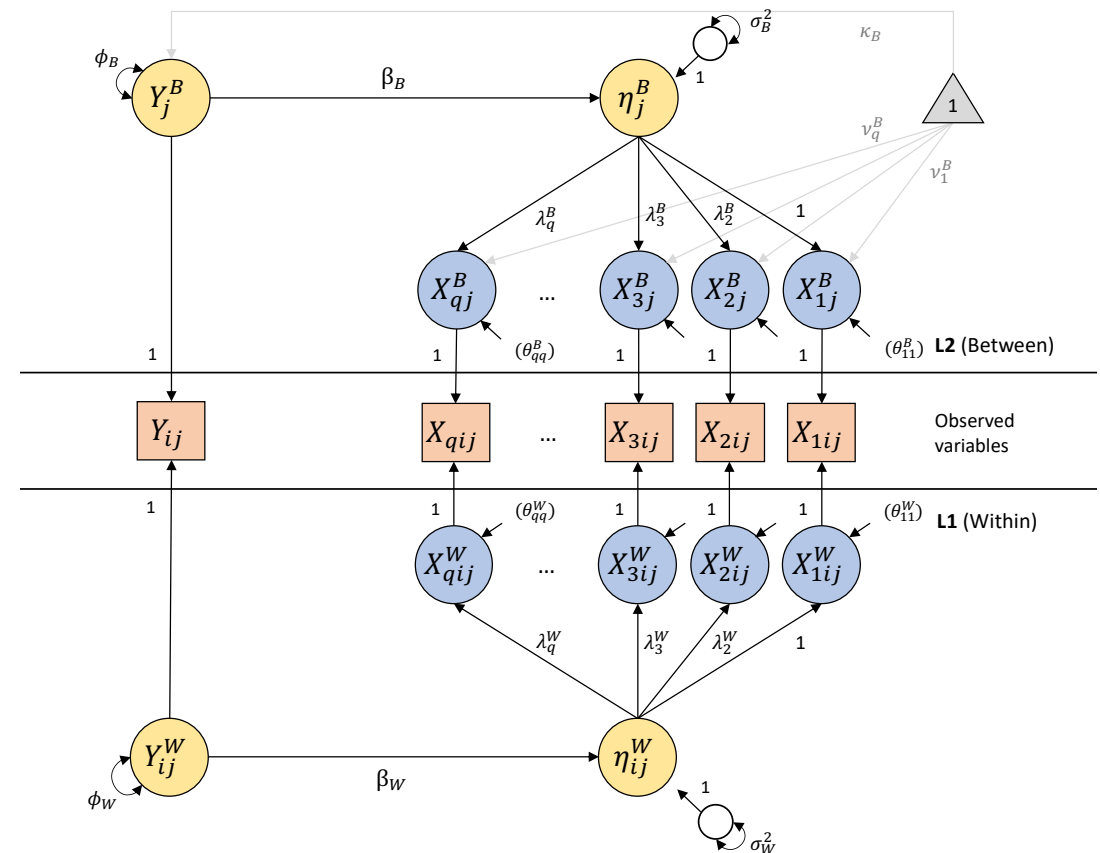
Introduction

Synthesizing Group Composition Effects from Complex Survey Data (ILSA)

Blömeke et al., (2021)



Marsh et al., (2009)

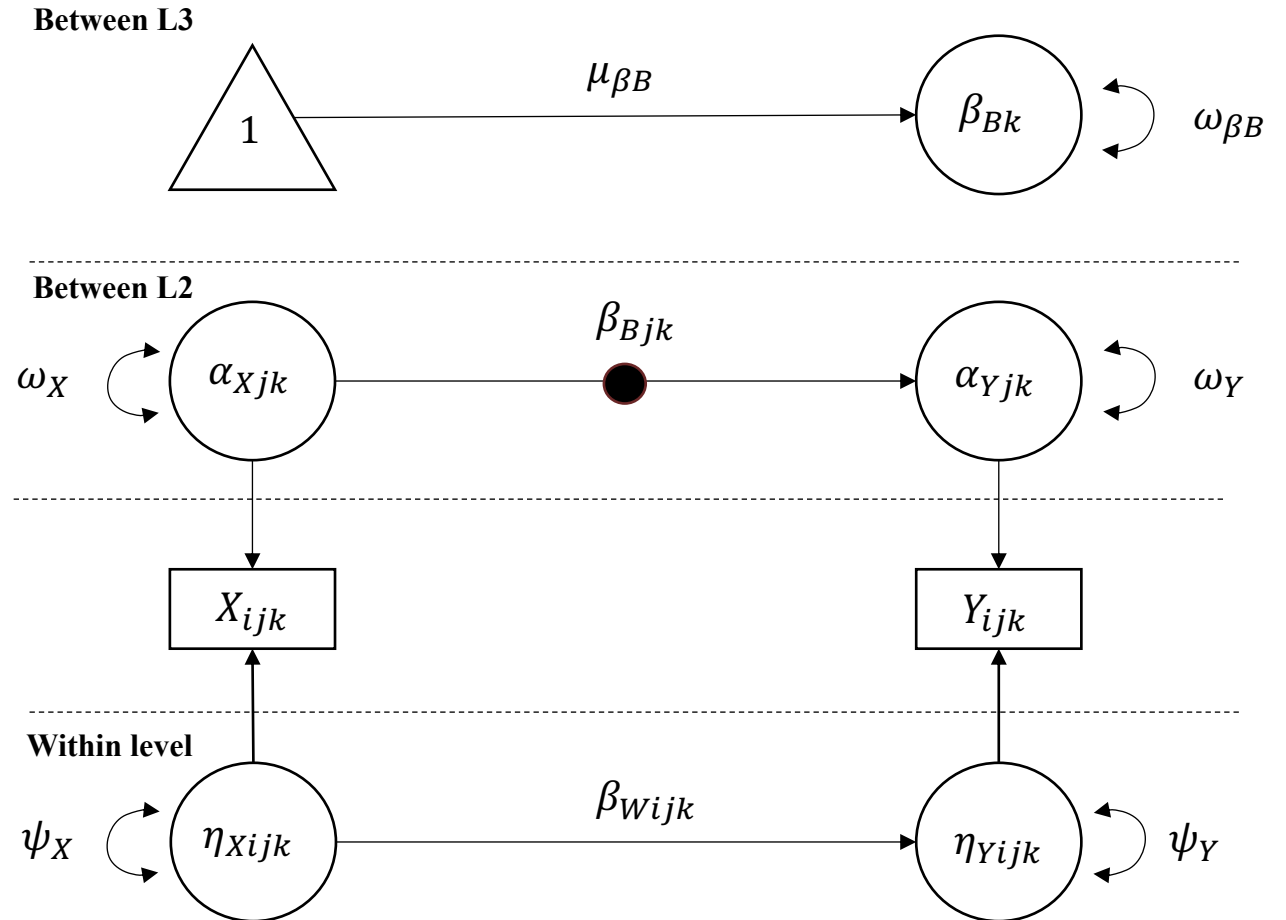


(Campos & Scherer, 2022; Keller et al., 2021; Strello, et al., 2022)

Introduction

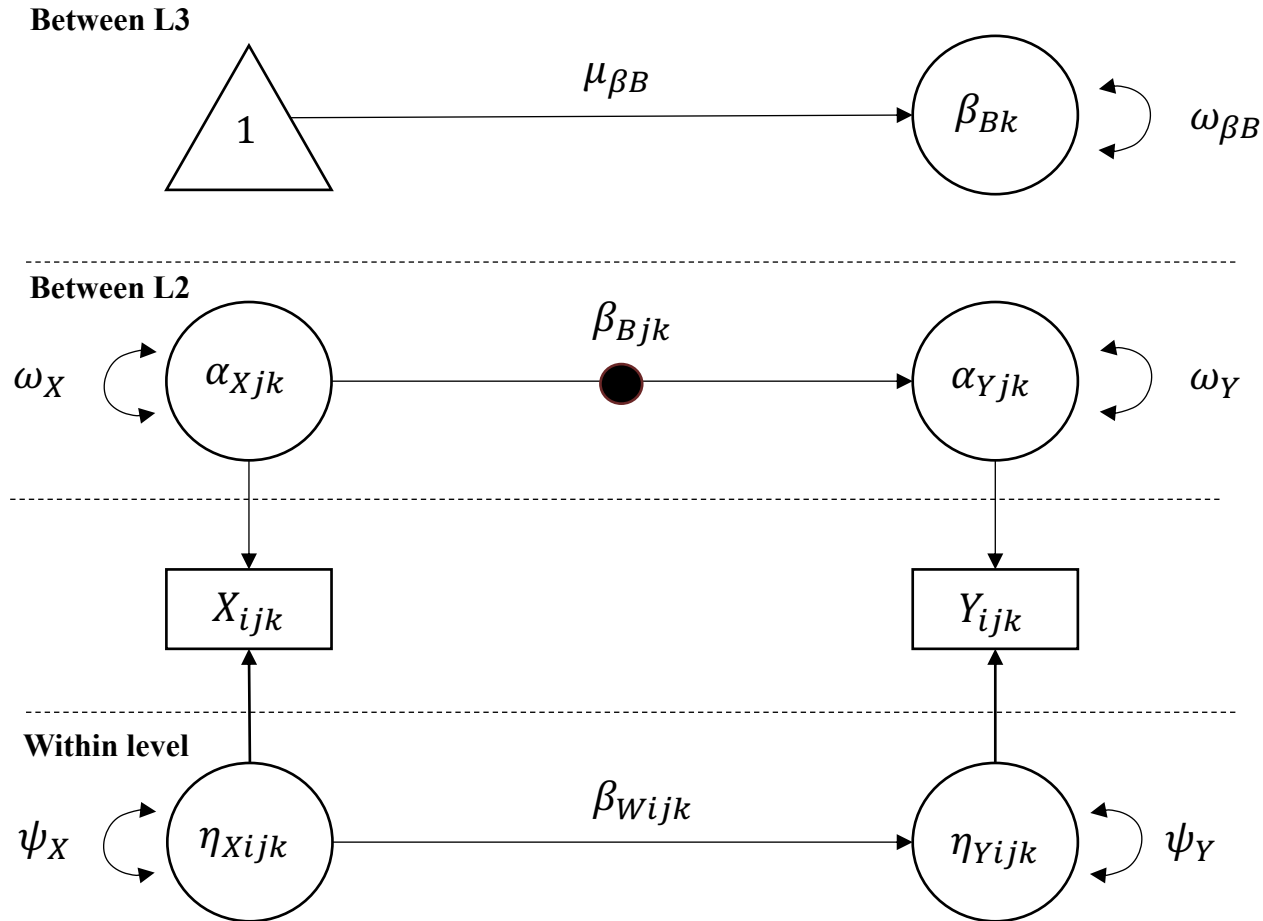
Synthesizing Group Composition Effects from Complex Survey Data (ILSA)

The contextual effect of school socioeconomic (SES) composition on student achievement



Introduction

Synthesizing Group Composition Effects from Complex Survey Data (ILSA)



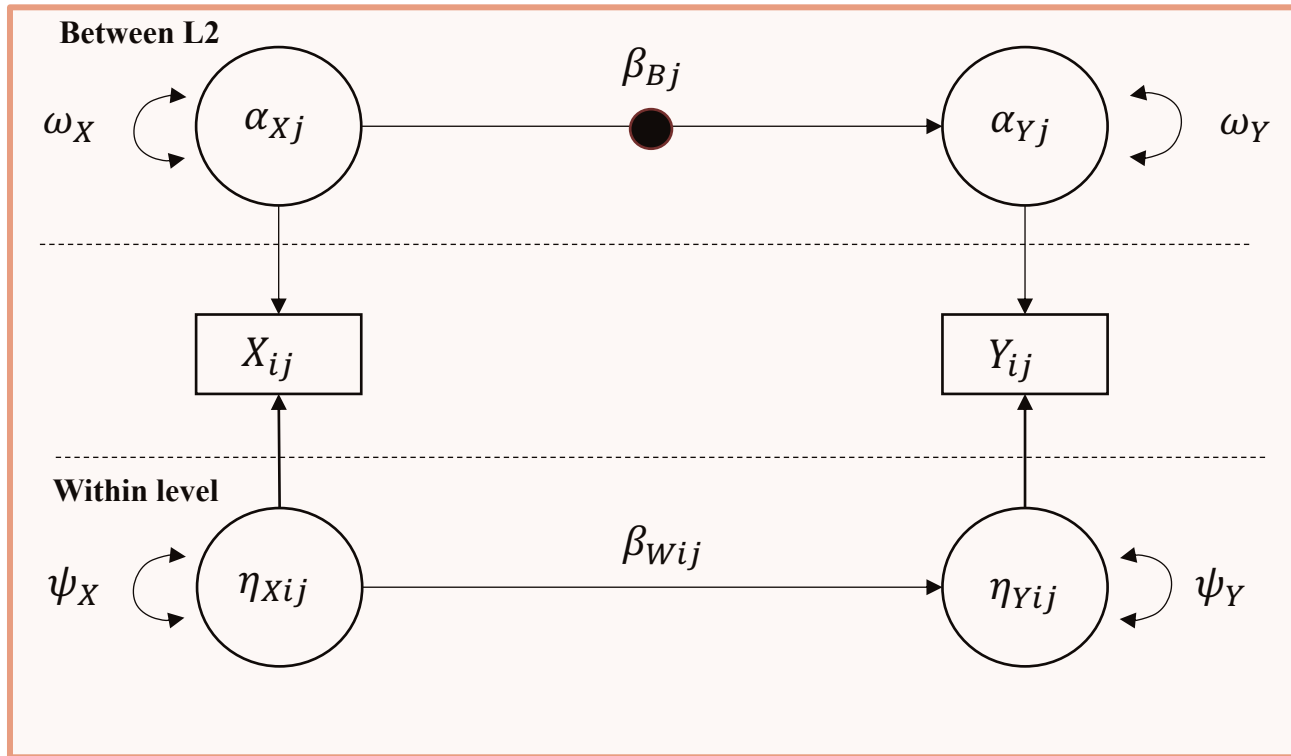
- Models are not currently available
- Model fit
- Model evaluation
- Computational intensive

Preacher, (2011).; Rockwood, (2020)

Introduction

Two-Stage IPD Meta-Analyses: Synthesis of SES composition effects

Stage 1: Raw Data Analysis



Stage 2: Meta-Analysis

- Multivariate meta-analysis
- Multilevel meta-analysis
- Mixed-effects meta-regression

Introduction

Two-Stage IPD Meta-Analyses

1. Standardized analyses across studies
2. Direct and model-based generation of the effect sizes of interest
3. Appropriate handling of statistical dependencies in primary and meta-analytic data sets

Research Goals

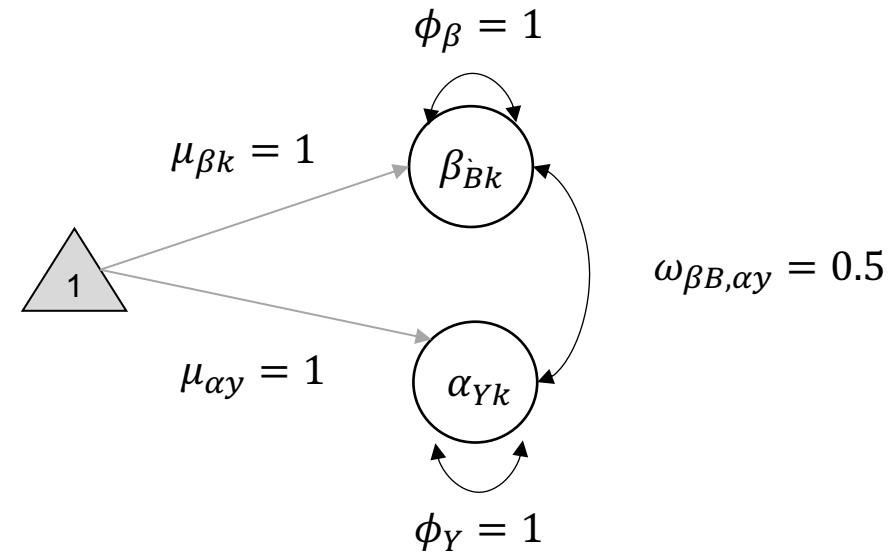
How well the two-stage parameter-based *MASEM* approach can approximate the “gold standard” (three-level random-slopes model) in the analysis of a level-2 direct effect that varies across level-3 units?

- Compare the convergence rates and estimates of the two-stage IPD meta-analysis and three-stage *MSEM* models for estimating contextual effects with random slopes.

Methodology

- 3-Level MSEM Model
- Two-stage IPD
 - Two-Level MSEM
 - Random-effects meta-analysis

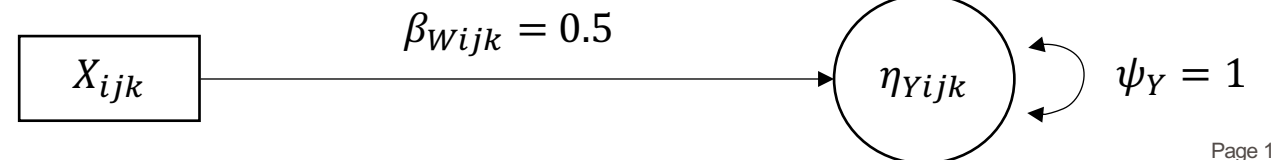
Between L3



Between L2



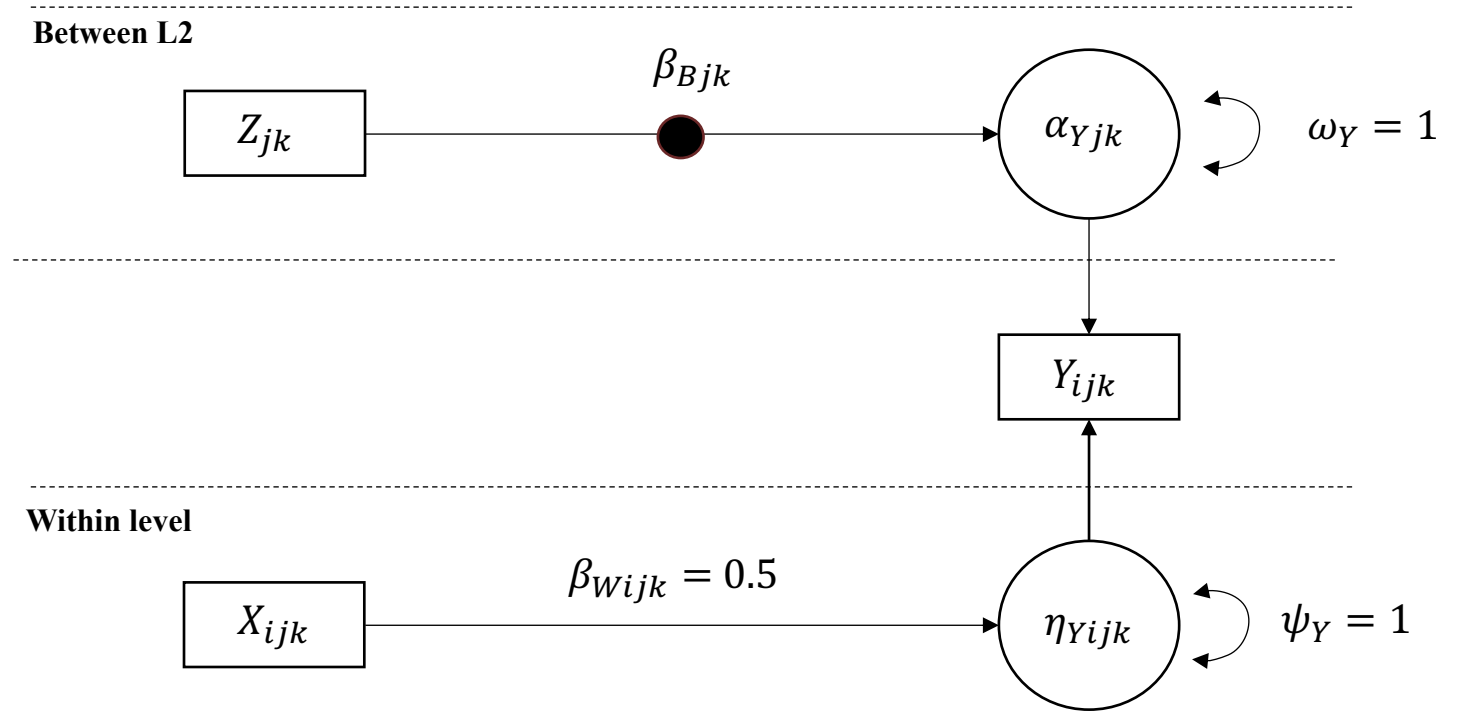
Within level



Methodology

- 3-Level MSEM Model
- Two-stage IPD
 - Two-Level MSEM
 - Random-effects meta-analysis

Step 1 – MSEM



Step 2 – Meta-analyse

$$y_i = \beta_0 + u_i + e_i$$

Methodology

L3	L2	L1	MISSING (Y)
25	50	5	0
50	100	10	0.1
75	200	15	0.2
		30	

- 1000 datasets were simulated from each of the $3 \times 3 \times 4 \times 3 = 108$ simulation conditions, resulting in a total of 108.000 datasets

Methodology

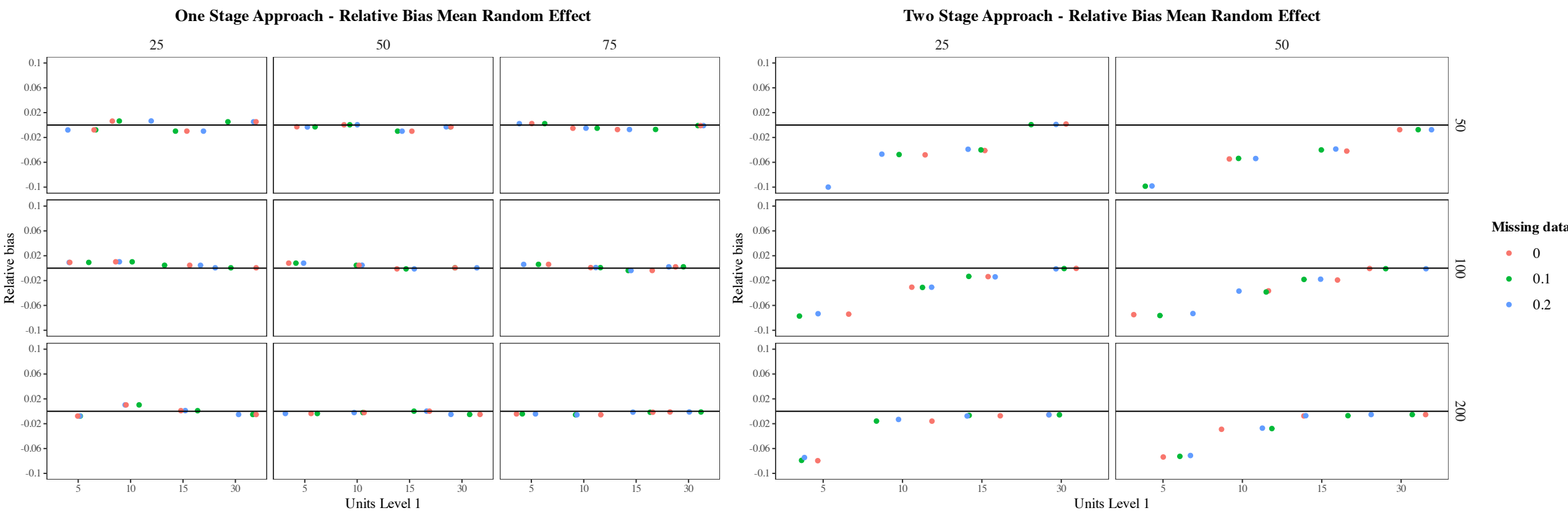
Evaluation Criteria

- **Convergence rate:** Output containing an error
- **Relative bias:** Average difference between the estimate and the population parameter
- **RMSE:** The average square difference between the model predicted estimates and the obtained parameter values
- **Coverage rate:** The proportion of times in which the true parameter is in the estimated 95% CI under each condition

Results

Comparison: Three-level MSEM and Two-Stage IPD MSEM

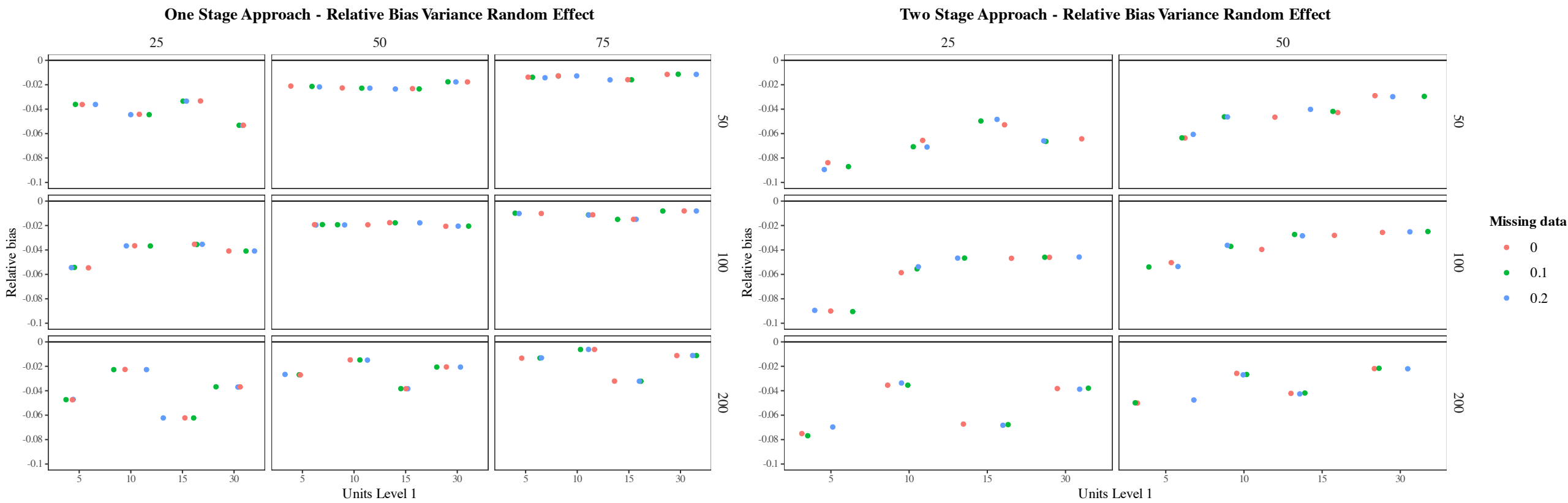
Relative Bias:



Results

Comparison: Three-level MSEM and Two-Stage IPD MSEM

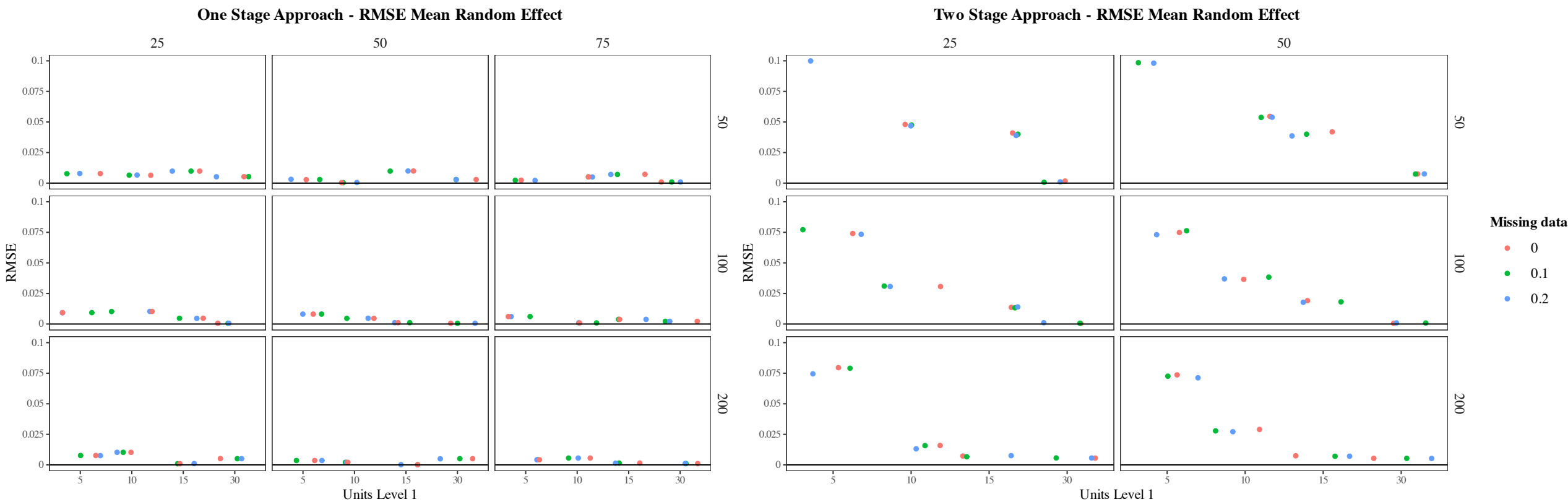
Relative Bias:



Results

Comparison: Three-level MSEM and Two-Stage IPD MSEM

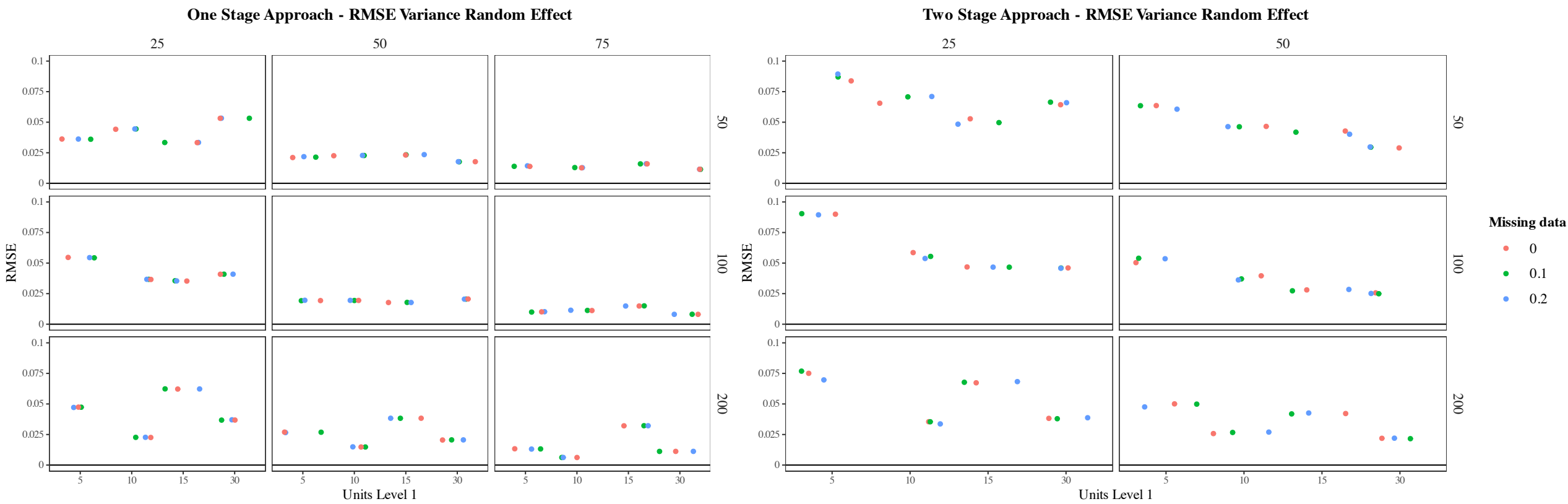
RMSE:



Results

Comparison: Three-level MSEM and Two-Stage IPD MSEM

RMSE:



Conclusions

- Estimates from the one-stage and two-stage IPD approach approach closely resemble the estimates from the population model.
 - In the two-stage IPD approach, the higher number of L3 units the closer estimate to the population parameter.
- The two-stage IPD approach is a viable alternative for the synthesis of group effects that overcomes the convergence problems, systematic bias, and computational issues of three-level MSEM models.
- Explore whether there are conditions under which the two-stage IPD would outperform the gold standard.

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Thank You

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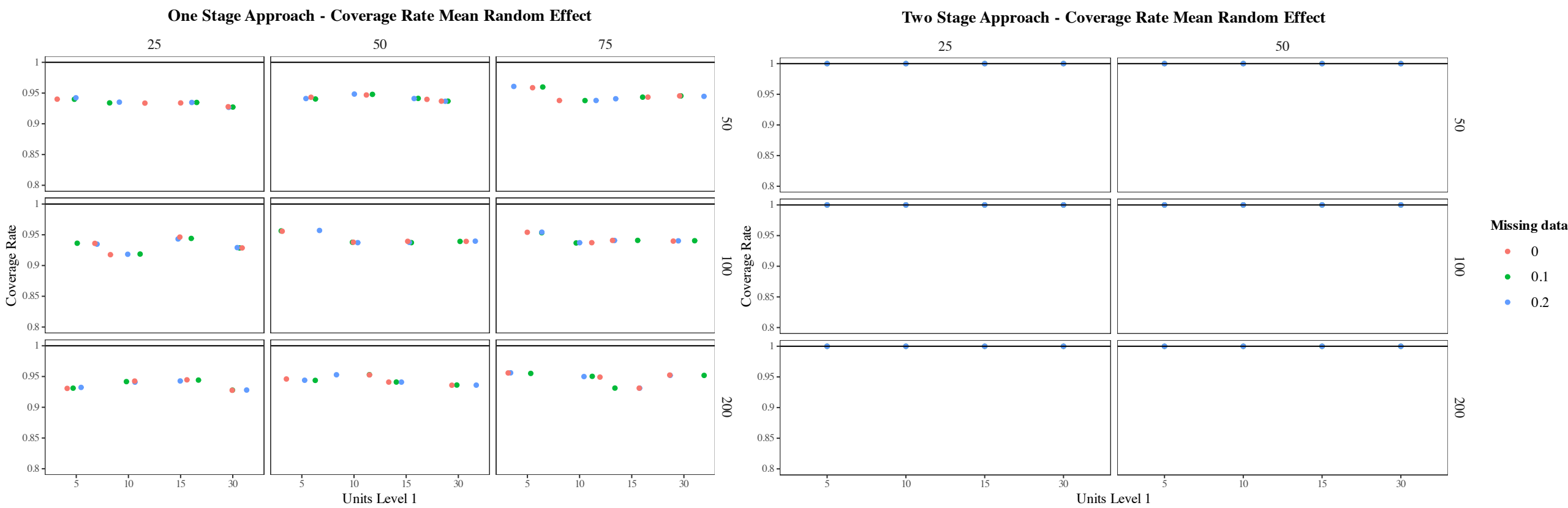
Methodology

- **Study 1:** How close is the performance of the two-stage IPD to the gold standard?
- **Study 2:** Are there conditions in which the two-stage IPD would outperform the gold standard?
- **Application study: Example**

Results

Comparison: Three-level MSEM and Two-Stage IPD MSEM

Coverage Rate:



Results

Comparison: Three-level MSEM and Two-Stage IPD MSEM

Coverage Rate:

