

To PV or not PV

How to get random slopes with ILSA studies

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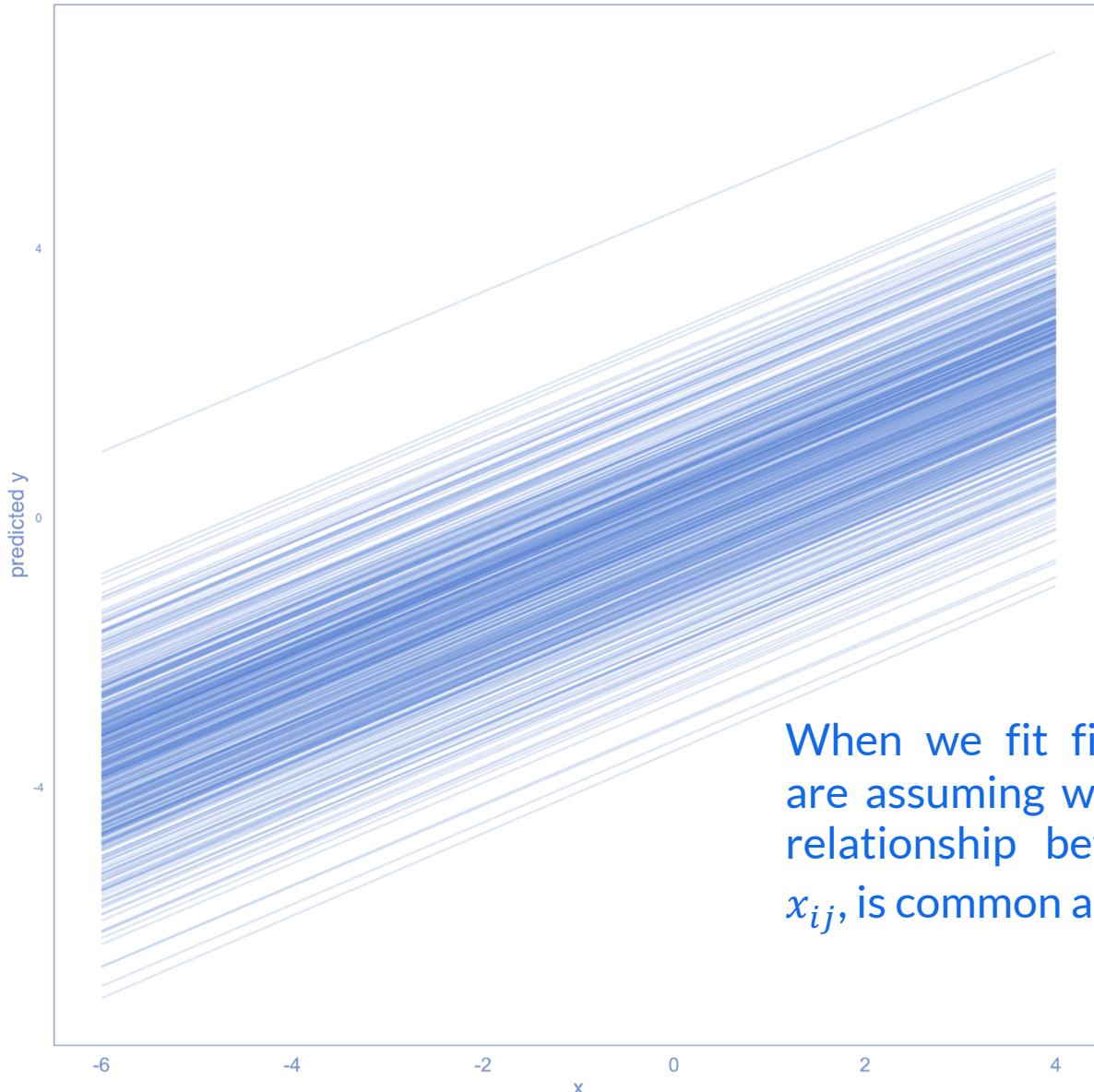
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Introduction

School variability and random slopes

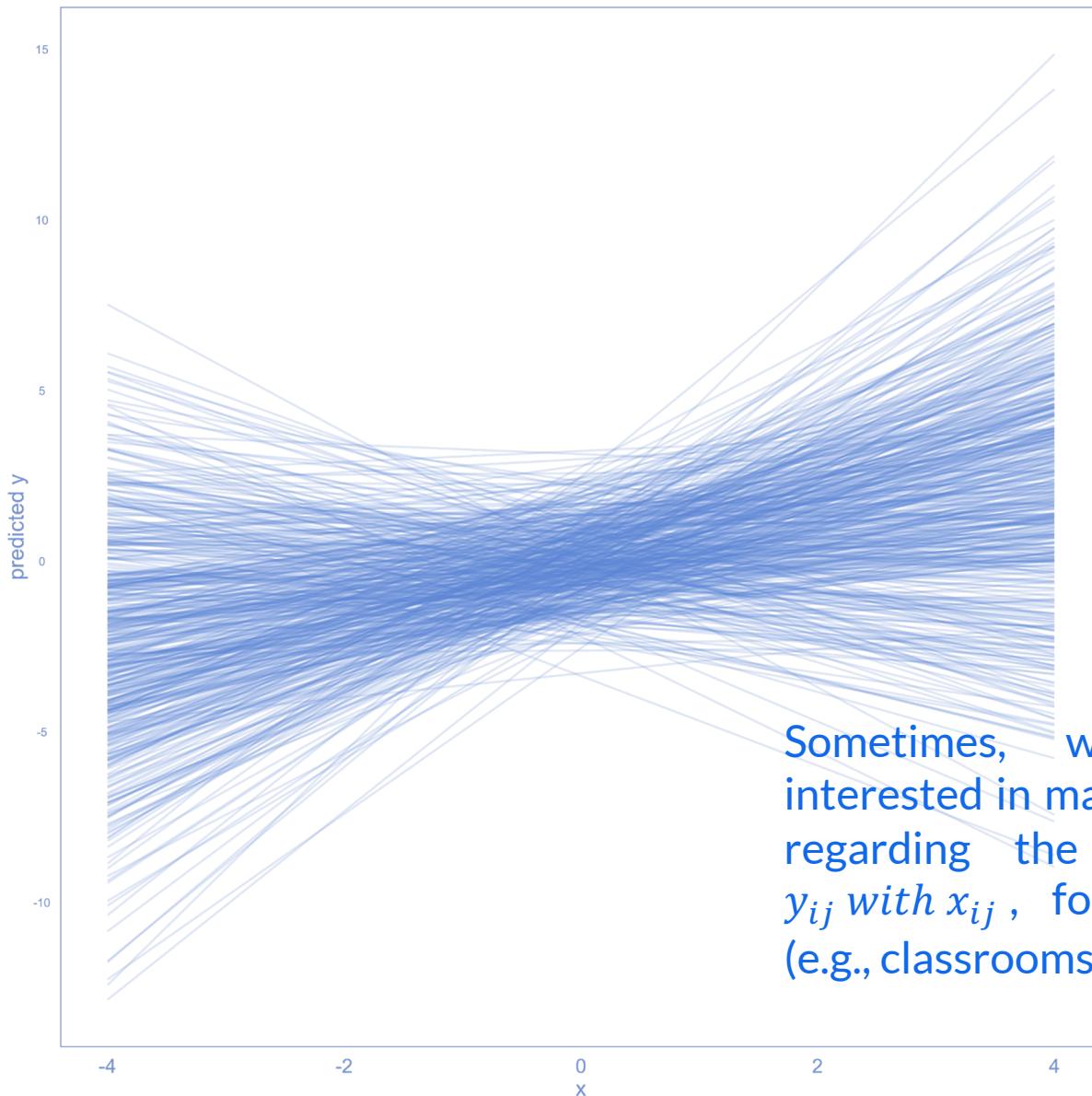
Introduction

How fixed slopes looks like



Introduction

How random slope looks like



Introduction

Random Slopes in Large Scale assessment

Random slopes are of special interest in the study of school effectiveness research

- Specially for **compensatory hypothesis** (e.g., Campbell, 2008)
 - Are there school factors that can ameliorate the socioeconomic gap?
- And also, for **differential effectiveness** research questions (e.g., Caro et al., 2016)
 - Are there any teacher practices that benefit students differently?

Large scale assessment studies are **ideal scenario** for these research inquiries

- These includes a **large collection of schools/classrooms** (150 or more), with a **sampling design** that can maximize variance of interest
- Yet, there is a **caveat** regarding the scores of interest
 - Test scores are represented with **plausible values**.

Problem

**Limitations of the
Plausible values**

Problem

Random slopes are not easily retrievable

Test outcomes scores in ILSA are very special

- Test outcomes are represented by **Plausible values**
- Plausible values are response **model realizations** (Wu, 2005)
- These can help us to retrieve expected population estimates of **congenial models** (i.e., nested models onto the generative model for the realizations) (Braun et al., 2017).
 - Yet, if the researcher model is not congenial, the obtained estimates may not recover the estimands he or she is looking for.
 - Specially, random slopes and interaction terms.
- Current conditional models used to generate plausible values **do not include terms to represent slope variabilities** (Zheng, 2024).
 - As such, model fitted onto the plausible values would not “recover” the expected random slopes estimates and variance.

This limitation compromise different research strands such as:

- **Compensatory hypothesis** (e.g., Campbell, 2008), **Differential Effectiveness hypothesis** (e.g., Caro et al, 2016), ... among other research inquiries that requires random slopes fitted onto plausible values.

Method

How are we going to
illustrate the problem?

Illustration

Plausible Values are not a good tool to retrieve random slopes

Methods

- To illustrate the problem we are pointing out, we will use data from International Civic and Citizenship Education Study 2009 (ICCS 2009).
 - We will fit a series of mixed models including civic knowledge as the response variable. We will use sex and socioeconomic status (ses) as covariates for different models, for each country. We will fit models of the following form:

$$y_{ij} = \alpha + \beta_{1j}(x_{ij} - \bar{x}_{.j}) + u_{0j} + u_{1j}(x_{ij} - \bar{x}_{.j}) + \epsilon_{ij}$$

- We will fit the model of interest **onto the five plausible values** as common guidelines would suggest (Von Davier et al., 2009; Rutkowski et al., 2010; Carsten et al., 2010).
 - We will use a Likelihood Ratio test adapted for imputed data (Grund et al., 2023) to make inferences regarding the random slope variance.
- We will proceed similarly, fitting the same model onto the IRT WLE scores also shared by the ICCS 2009 study (i.e., NWLCIV scores).
- We standardized estimates using the score respective standard deviation (PV = 100, WLE = 10).

Illustration

Plausible Values are not a good tool to retrieve random slopes

Rationale

- The IRT WLE scores are expected to not to be affected by the limitations of the conditioning model.
- IRT WLE scores do not carry the measurement model error or uncertainty, yet these may provide attenuated estimates (Bhaktha et al, 2021).
- However, if these scores are generated with (Diakow, 2013)
 - A large number of items (e.g. more than 25 items)
 - Present high reliability
 - And good spread of item locations (i.e., high test information coverage)
 - These bias should be ameliorated.
- IRT WLE from ICCS 2009 fulfill all these requirements (i.e., generated with 79 items, with a good spreading of difficulties, and high reliability ($> .8$) (See Schulz et al., 2011),
- Thus, comparing the results of models fitted onto PV scores, and onto IRT WLE scores can give use an approximation of how risky is to rely on PV scores alone when our research inquiry requires random slopes.

Results I

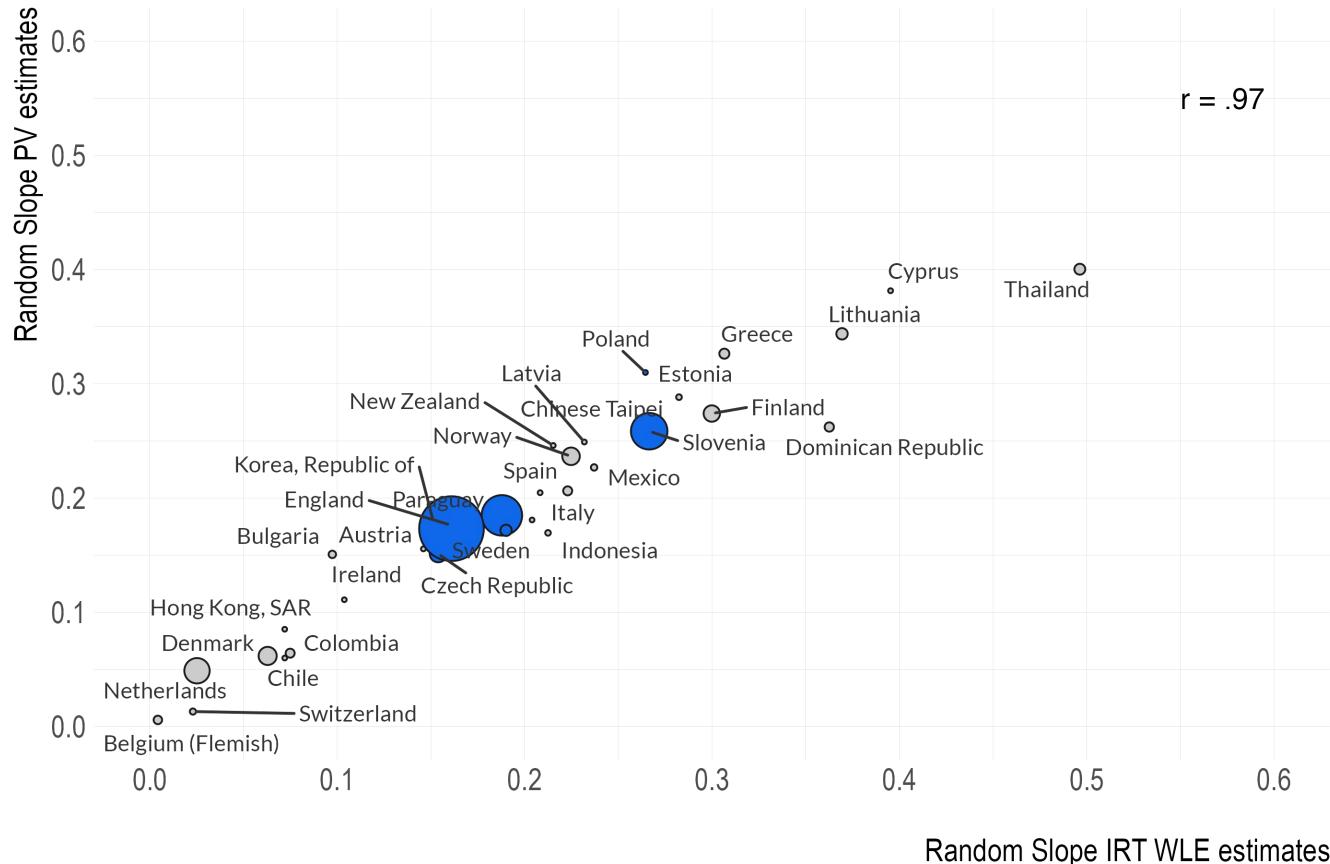
**Random slopes for gender
gaps**

Random Slopes

Gender gaps on civic knowledge

Random slopes for gender gaps on civic knowledge

ICCS 2009 (highlighting PV estimates)



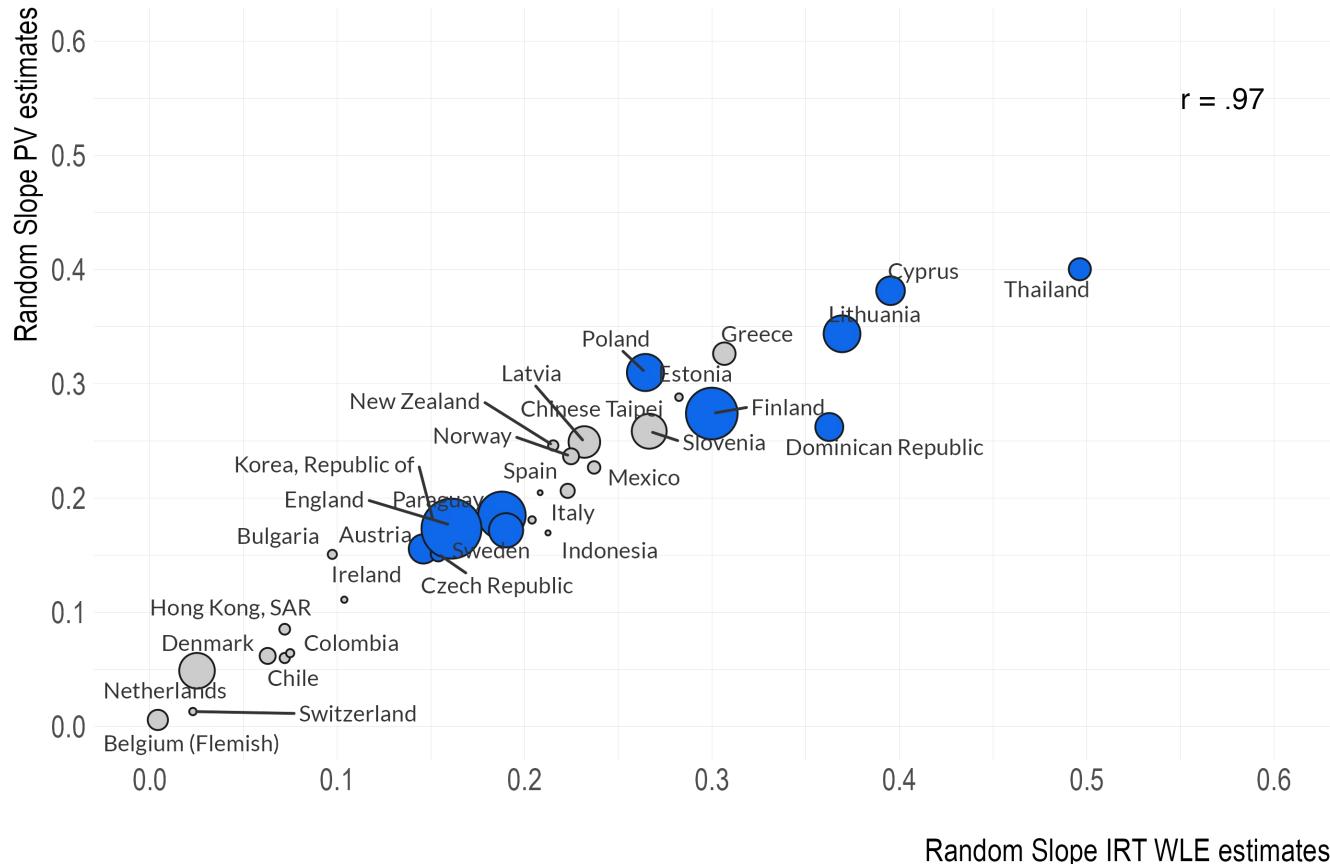
Note: blue dots highlights random slopes via D2 stat for PV (Grund et al., 2023); bubble size is relative variance of the random slope.

Random Slopes

Gender gaps on civic knowledge

Random slopes for gender gaps on civic knowledge

ICCS 2009 (highlighting IRT WLE estimates)



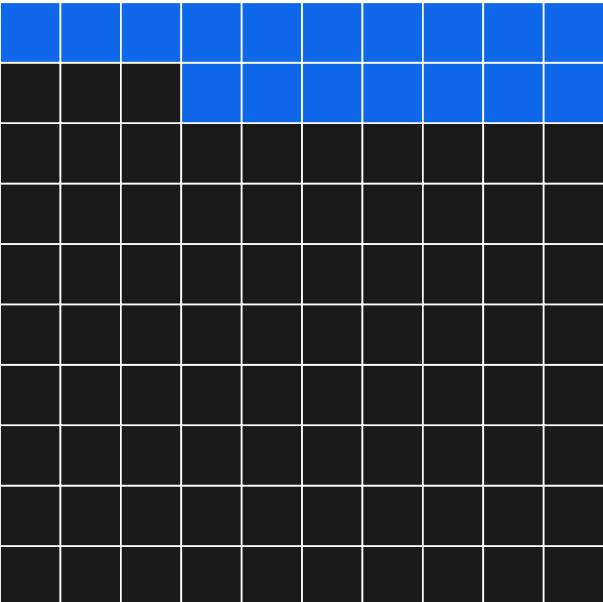
Note: blue dots highlights random slopes via LRT mixture on IRT WLE scores; bubble size is relative variance of the random slope.

Random Slopes

Gender gaps on civic knowledge

Estimates with Plausible Values

D2 stat (Grund, 2023), 6 of 35 are random

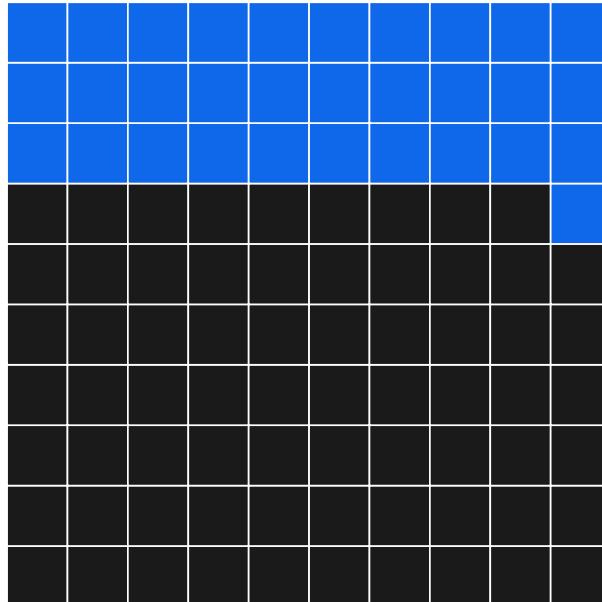


■ Fixed slope (83%)

■ Random slope (17%)

Estimates with IRT WLE scores

LRT mixture, 11 of 35 are random



■ Fixed slope (69%)

■ Random slope (31%)

Results II

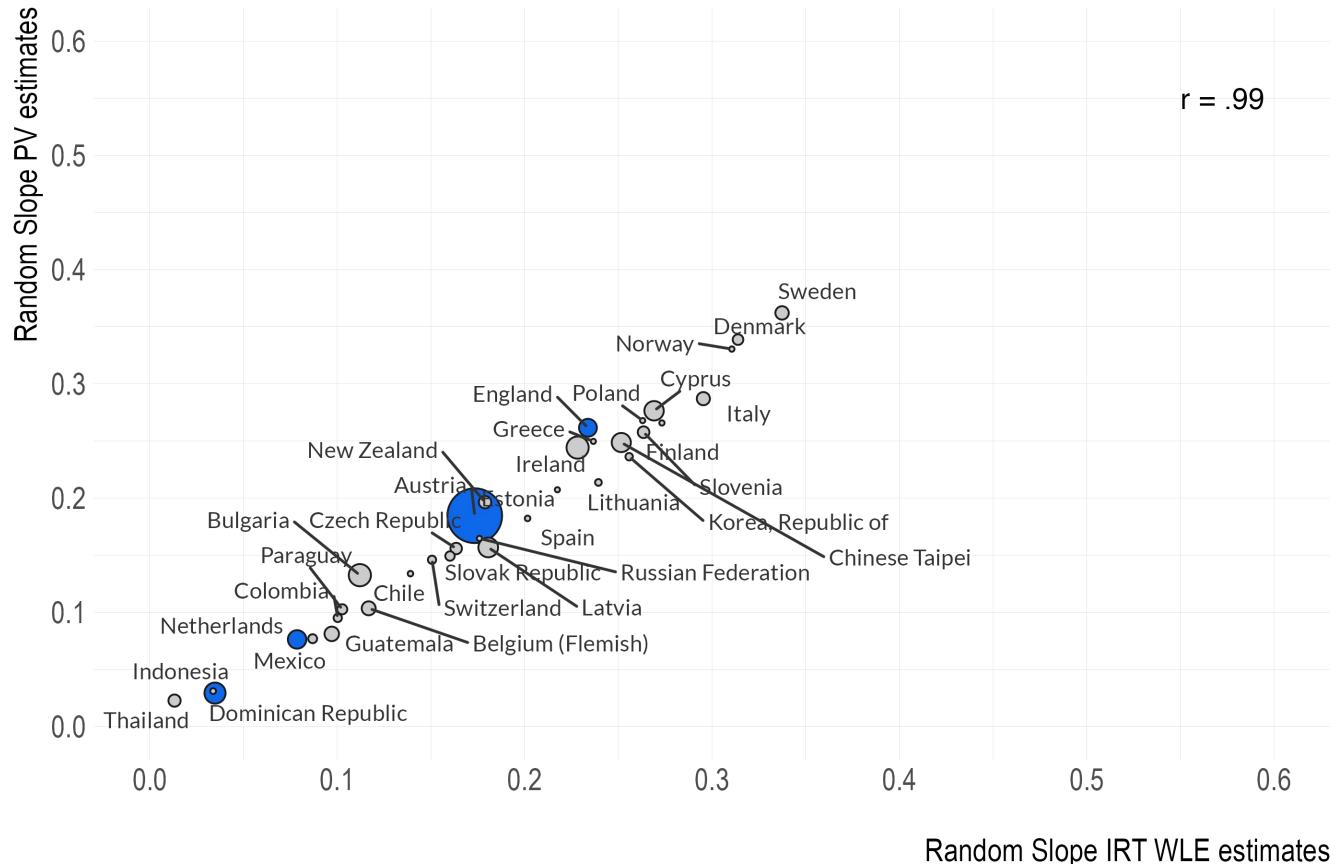
**Random slopes for
socioeconomic gaps**

Random Slopes

SES gaps on civic knowledge

Random slopes for SES gaps on civic knowledge

ICCS 2009 (highlighting PV estimates)



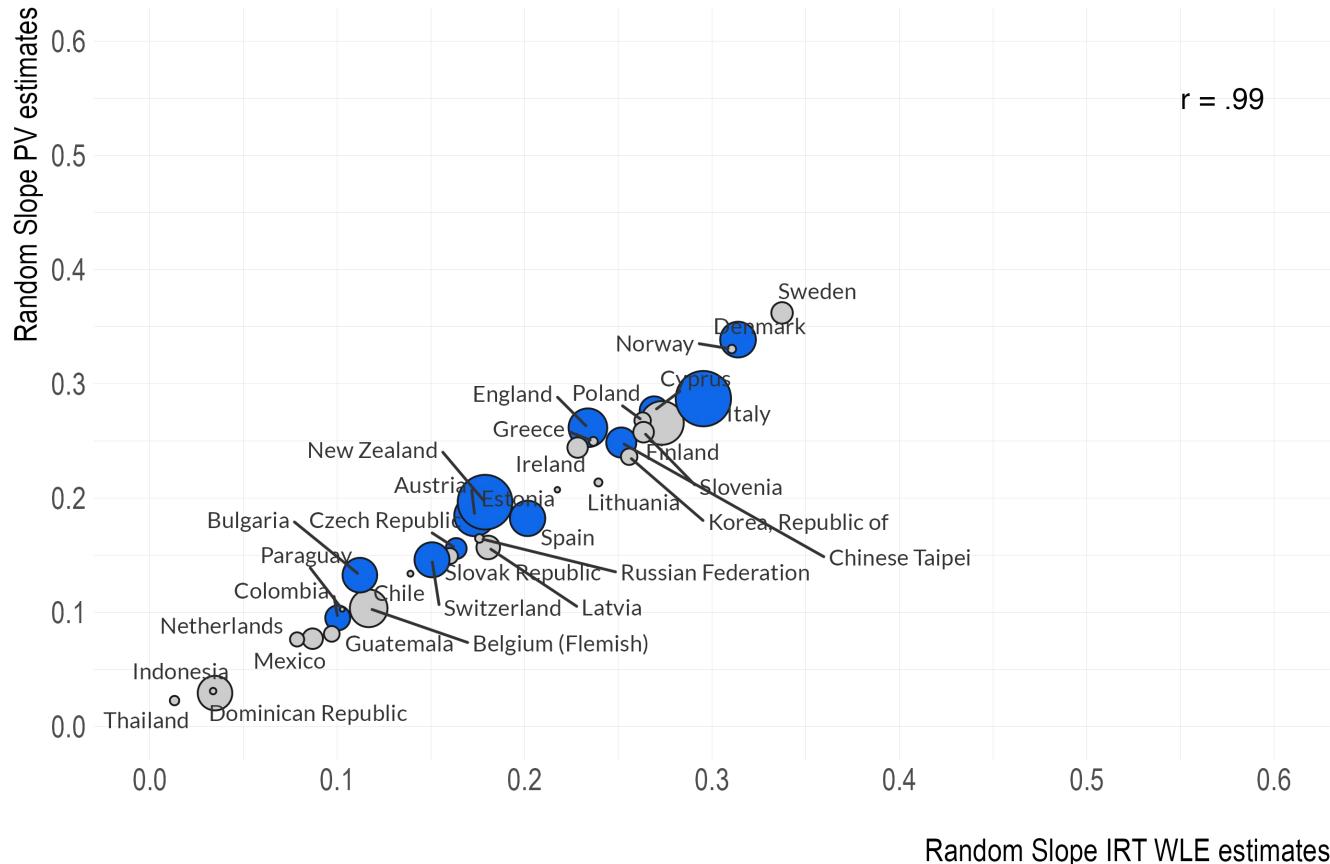
Note: blue dots highlights random slopes via D2 stat for PV (Grund et al., 2023); bubble size is relative variance of the random slope.

Random Slopes

SES gaps on civic knowledge

Random slopes for SES gaps on civic knowledge

ICCS 2009 (highlighting IRT WLE estimates)



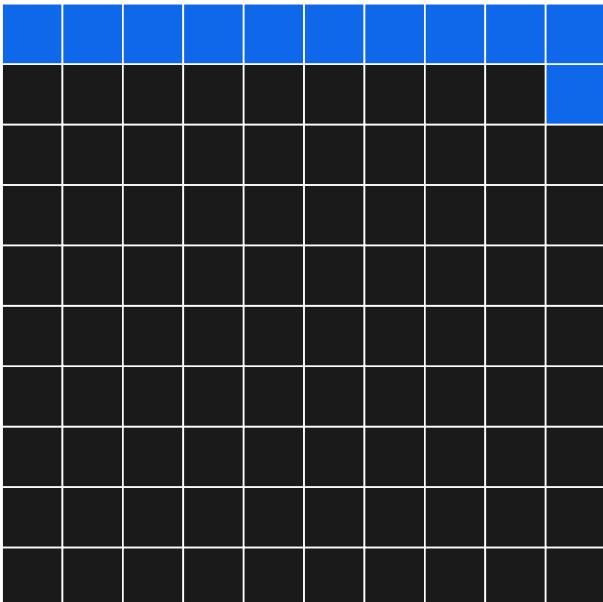
Note: blue dots highlights random slopes via LRT mixture on IRT WLE scores; bubble size is relative variance of the random slope.

Random Slopes

SES gaps on civic knowledge

Estimates with Plausible Values

D2 stat (Grund, 2023), 4 of 35 are random

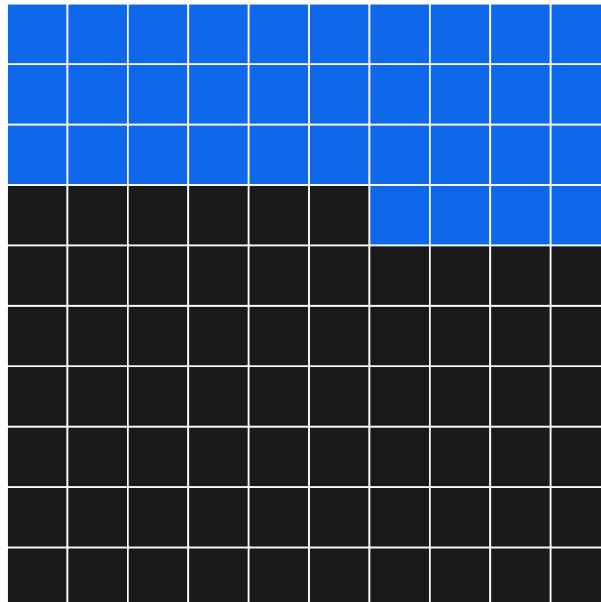


■ Fixed slope (89%)

■ Random slope (11%)

Estimates with IRT WLE scores

LRT mixture, 12 of 35 are random



■ Fixed slope (66%)

■ Random slope (34%)

Discussion Summary and take-home message

Summary

Random slopes estimates with large scale assessment

Conclusion

- Random Slope estimated with **PV scores** are compromised.
- These do not recover the variance of the random slope estimates (Zheng, 2024).
- For the current study, **is 2 to 3 times more likely to recover random slopes when using IRT WLE scores**, than when using PV scores, for the chosen covariates.
- If the test has a good number of items, well spread item locations and high reliability, an alternative approach is to **produce random slope estimates with the IRT WLE scores** of the target test.

Summary

Random slopes estimates with large scale assessment

Take home message for secondary users:

- For inquiry requiring random slopes random slopes estimates using PV scores seems to underestimate the estimates variance
- If available, a better choice is to use the IRT WLE scores for the same purpose
- If not available, we could either:
 - Generate the IRT WLE scores first, and fit models with these new scores
 - Fit a full fledge explanatory response model, including the desire random slope
 - Bear in mind, the time needed to fit these models; which might be larger than fitting random slope models onto observed scores.

Summary

Random slopes estimates with large scale assessment

Take home message for ILSA providers:

- PV scores aid the generation of results for many of research inquiries of interest.
- Yet, these may distort inferences outside the space of the congenial models.
- An easy aid for secondary users is to provide the IRT WLE scores of the target test, and its standard errors.
 - These two elements may help researchers to retrieve estimates of interest outside the congenial space of the conditional models of the generated plausible values (Diakow, 2013).

Further research

- Complement the present results with simulations to identify size of bias, and other edge conditions (e.g., estimate size, variance size, floor and ceiling effects of test item locations).

Grazie mille!

References

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