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# Meta-Analyzing International Large-Scale Assessment Data: An Application of the Split, Analyze, and Meta-Analyze (SAM) Approach

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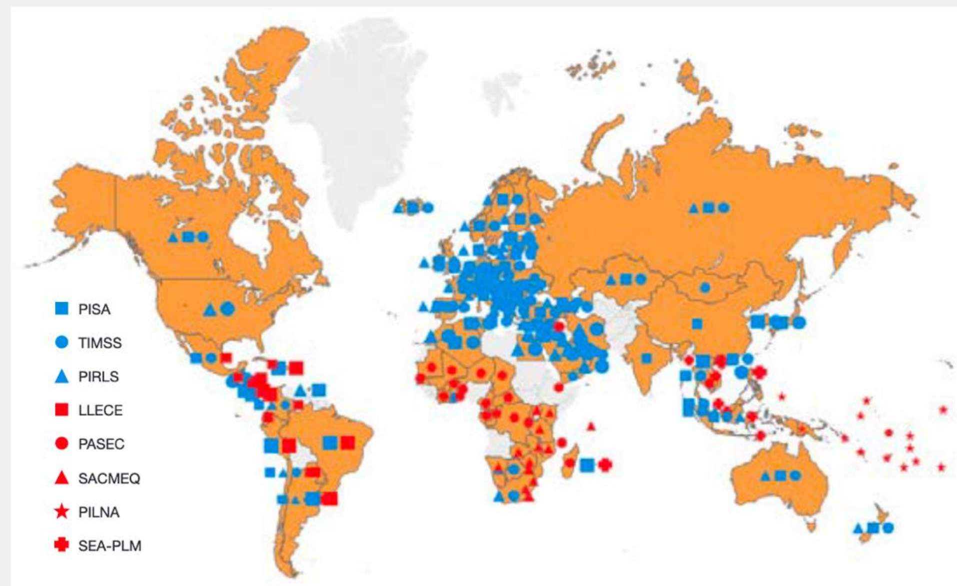
# Background

Regional, national, and international educational assessments are increasing around the world

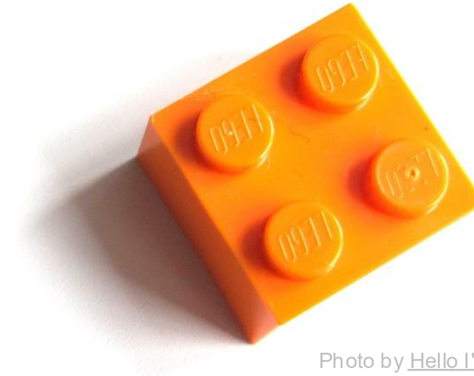
**Figure 2.2 School-based assessment**




**Note:** Areas shaded in orange correspond to the existence of national assessments.
*Source: UNESCO Institute for Statistics (UIS).*

UNESCO, (2018)

# Background



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Large-scale educational assessments provide data of students, classrooms, and schools that can be used to:

- Test hypotheses about relations among constructs
- Study differences between groups
- Attempt large-scale replications

## Advantages

- Representative probability samples
- Standardized measurements

OECD, (2017)

# Background

- The assessments have not been considered in most meta-analyses

  Holzberger, Reinhold, Lüdtke, Seidel (2020)
  Keller, L., Preckel, F., & Brunner, M. (2021)

- Methodological choices in the analysis of the data lead to substantially different results

  Mittal, Nilsen, & Björnsson (2020)

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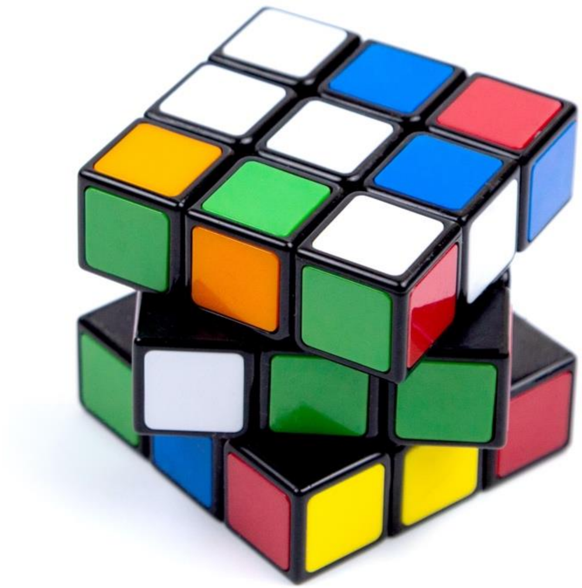
# Background

## Challenges for the meta-analyses

1. Cluster sampling
   - Primary nesting
   - Secondary nesting
2. Unequal selection probability
3. Plausible values
4. Comparability across countries



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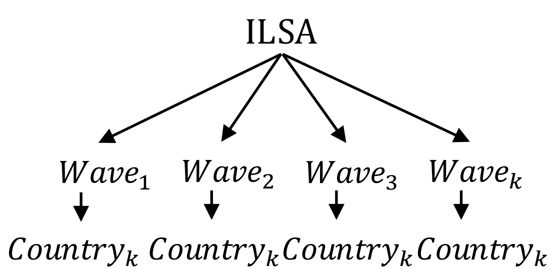
Rutkowski, Gonzalez, Joncas, von Davier (2010)

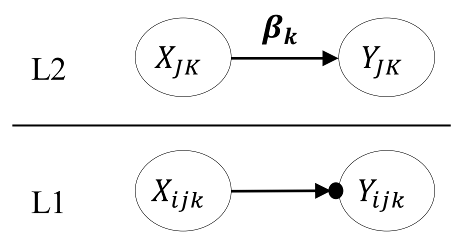
# Three steps to meta-analyse ILSA data

## Individual Participant Data Meta-analysis

### Step 1 – Split




### Step 2 – Analyse




- Hierarhical structure
- Sampling weights
- Plausible values
- Measurement Invariance

### Step 3 – Meta-analyse

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

Cheung & Jack (2016)

# Illustrative Case

We aimed to study the generalizability of the **Big-Fish-Little-Pond-Effect (BFLPE)** across countries and TIMSS waves

- RQ1: To what extent does evidence support the generalizability of the BFLPE across countries?
- RQ2: To what extent do country-level variables (Human development index, individualism, power distance, uncertainty avoidance, masculinity, indulgence, and long-term orientation) explain the variation in the BFLPE across countries?

# Method

Five TIMSS cycles 2003, 2007, 2011, 2015, and 2019

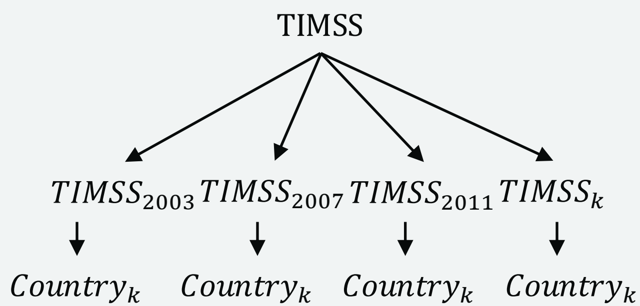
- All the participating countries
- Fourth-grade data only

**Table 1**
*Sample size*

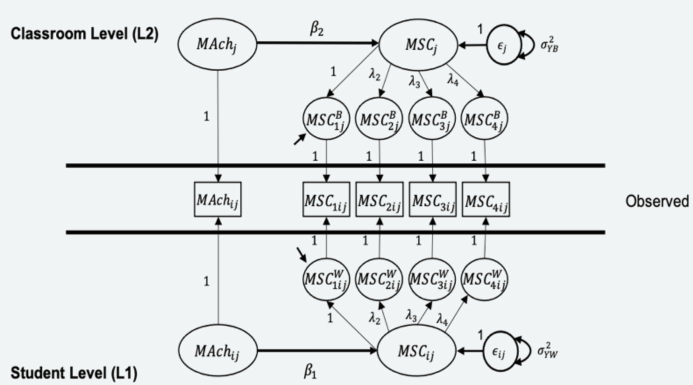
| | Countries | Sample Size |
|---|---|---|
| ILSA Cycle | | |
| TIMSS 2003 | 29 | 123815 |
| TIMSS 2007 | 44 | 182488 |
| TIMSS 2011 | 55 | 277493 |
| TIMSS 2015 | 56 | 323299 |
| TIMSS 2019 | 64 | 330191 |
| Meta-analysis | | |
| Model | **85** | **248** |

# Data Analysis

**Step 1 Split**



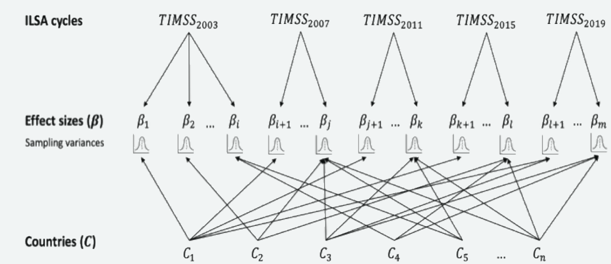

**Step 2 Analyse**



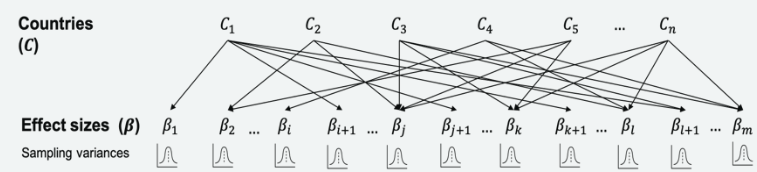

$$ES_{BFLPE} = 2 \times (\beta_j - \beta_i) \times \sigma_{yj} / \sigma_{yij}$$

**Step 3 Meta-analyse**

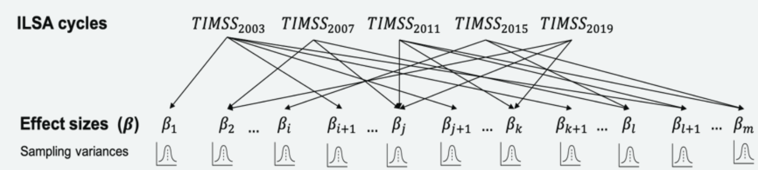
## Cross-classified random-effects model




## Three-level model - Countries




## Three-level model – Cycles



# Results Meta-Analysis – Comparison working models

**Table 3**

*Comparison of meta-analytic models*

| | $\hat{\mu}$ [CI] | $\sigma^2_{(1)}$ | $\sigma^2_{(2)}$ | $\sigma^2_{(3)}$ | $I^2$ | $I^2_{(2)}$ | $I^2_{(3)}$ |
|---|---|---|---|---|---|---|---|
| Random-effects model | -.458 [-.480, -.435] | .025 [.02, .03] | | | 82.43% | - | - |
| Three-level Waves | -.458 [-.484, -.432] | - | .025 [.020, .031] | .000 [.000, .002] | - | 82.43% | 0% |
| Three-level Countries | -.451 [-.486, -.416] | - | .004 [.002, .006] | .021 [.014, .031] | - | 12.06% | 69.97% |
| Cross-classified | -.452 [-.489, -.415] | .020 [.014, .031] | .003 [.001, .006] | .000 [.000, .002] | 70.58% | 10.87% | 0.69% |

- The estimated average effect size is similar across the working models
- Ignoring the nesting merge the variance associated to variation in the effect sizes and countries
- TIMSS nesting does not seem to explain variance in the effect sizes

# Results Meta-Analysis – Comparison working models

- The three-level waves model had a better fit than the cross-classified random effects model $\chi^2(3) = 117.843\ p < 0.0001$
- The cross-classified random effects model and the three-level countries model showed similar fit $\chi^2(3) = 1.665\ \ p = 0.197$
- There is no gain when adding the between-waves variation

# Results - Three-level mixed-effects meta-regression

The cultural characteristics did not explain the heterogeneity in the effect sizes

**Table 4**

*Results multivariate mixed-effects meta-analysis - cultural variables*

| | Slope Coefficient | 95% CI | p-value |
|---|---|---|---|
| Intercept | -.137 | [-.561, .140] | .440 |
| Individualism - Collectivism | -.002 | [-.005, -.0002] | .142 |
| Masculinity-femininity | -.000 | [-.003, .002] | .492 |
| Power distance | -.002 | [-.006, .001] | .148 |
| Uncertainty avoidance | -.001 | [-.002, .001] | .276 |
| Indulgence-restraint | .002 | [-.001, .005] | .823 |
| Long-term vs. short-term orientation | .000 | [-.002, .002] | .795 |

# Results - Three-level mixed-effects meta-regression

The economic index did not explain the heterogeneity in the effect sizes

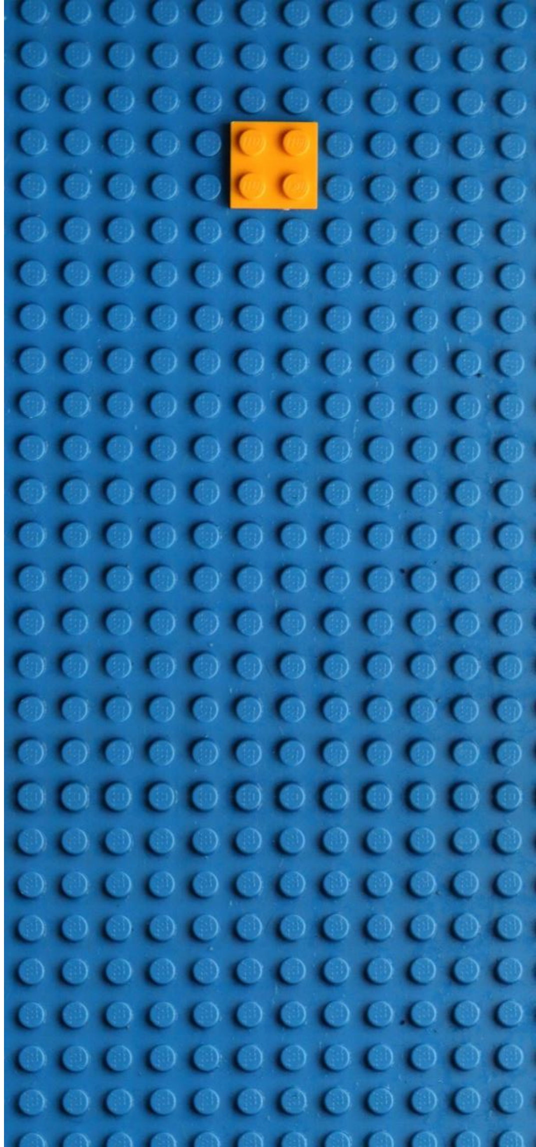
**Table 5**

*Results multivariate mixed-effects meta-analysis economic index*

| | Slope Coefficient | 95% CI | p-value |
|---|---|---|---|
| Intercept | -.812 | [-1.114, -.509] | <.0001 |
| Human Development Index | .426 | [.069, .782] | .107 |

# Conclusions

1. Cross-country differences and variation between effect sizes explain most of the heterogeneity in the BFLPE
2. Ignoring the nesting of the meta-analytic dataset conflate the variance associated with the effect sizes and the countries
3. ILSA cycles do not account for variance in the effect sizes



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# Conclusions

4. None of the country-level variables explain the heterogeneity between effect sizes

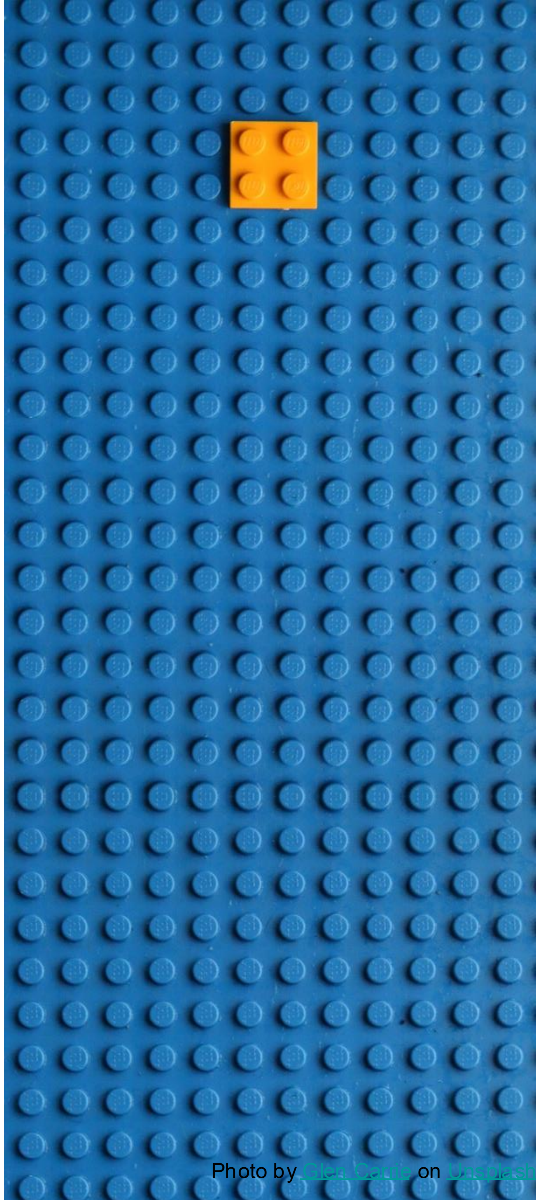

Photo by Glen Carrie on Unsplash

# Implications

1. The meta-analysis of ILSA studies has multiple benefits:
   - Derive multiple effect sizes
   - Test for the comparability of measures across groups
   - Test for the replicability of findings in high-quality data with representative samples

2. The SAM approach can be used to synthesize effect sizes from complex survey data

3. The meta-analysis of ILSA data must consider the methodological complexities of the ILSA and the nested structure of the meta-analytic dataset

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# Thank you!

# **Questions?**

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**Table 2.**

*Description Cultural Dimensions proposed by Hofstede et al. (2010)*

| Dimension | Description |
|---|---|
| Individualism-Collectivism | Refers to the extent to which people feel independent, rather than interdependent as members of larger groups. |
| Power distance | Denotes the degree to which nationals from a country accept and expect that power is distributed unequally. |
| Uncertainty avoidance | Indicates the degree to which members of a society are tolerant to uncertainty and ambiguity. |
| Masculinity-feminity | Specifies the extent to which the use of force is socially approved within a culture. |
| Long-term vs. short-term orientation | Reveals the degree to which a culture is focused on pragmatic solutions and adaptations to future challenges versus traditional solutions based on the past and traditions. |
| Indulgence-restraint | Identifies the degree to which a society allows or supress the gratification of needs related to enjoying life and having fun. |

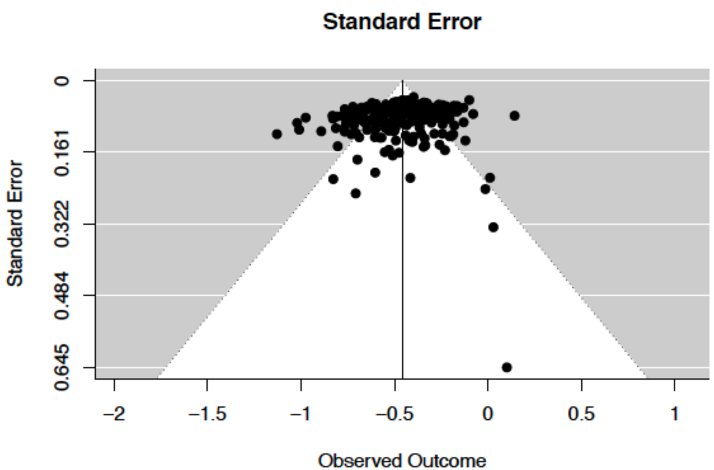
# Results – MG MCFA

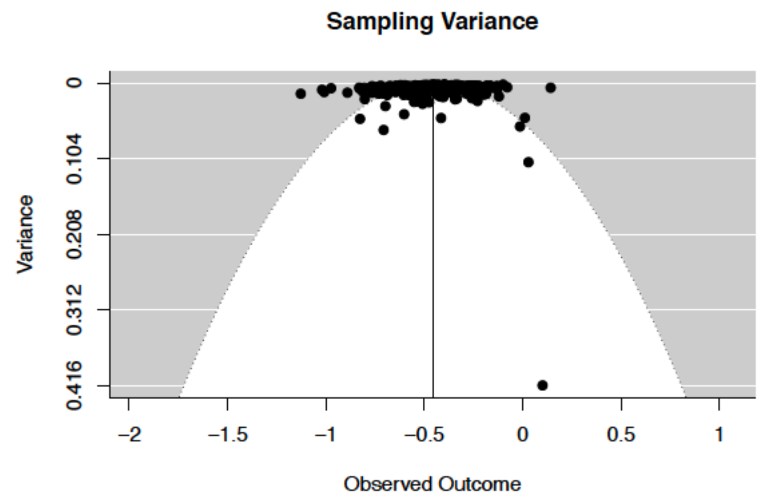
**Table 1**

*Fit statistics of the measurement invariance models (MG-MCFA)*

| | TIMSS 2003 | | | TIMSS 2007 | | | TIMSS 2011 | | | TIMSS 2015 | | | TIMSS 2019 | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Model | RMSEA | CFI | TLI | RMSEA | CFI | TLI | RMSEA | CFI | TLI | RMSEA | CFI | TLI | RMSEA | CFI | TLI |
| Configural model | .000 | .998 | 1.000 | .000 | .995 | 1.000 | .000 | .996 | 1.000 | .027 | 1.000 | .98 | .027 | 1.000 | .982 |
| L1 invariance model | .077 | .947 | .836 | .066 | .956 | .867 | .061 | .968 | .902 | .063 | .963 | .889 | .067 | .962 | .886 |
| L2 invariance model | .048 | .959 | .937 | .040 | .969 | .952 | .037 | .977 | .965 | .036 | .976 | .963 | .04 | .973 | .96 |
| L1 and L2 invariance model | .047 | .958 | .939 | .039 | .969 | .954 | .036 | .977 | .966 | .036 | .975 | .965 | .039 | .973 | .962 |
| Contextual model | .053 | .931 | .904 | .051 | .934 | .908 | .056 | .927 | .897 | .061 | .910 | .875 | .057 | .924 | .896 |

*Note.* Configural model: a model with one factor for mathematics self-concept and factor loadings allowed to vary across levels and countries. L1 invariance model: factor loadings restricted to be invariant across countries at L1. L2 invariance model: factor loadings are restricted to be invariant across countries at L1 and L2, but with factor loadings allowed to vary across levels. L1 and L2 Invariance Model: a model with factor loadings restricted to be invariant across countries and levels. The contextual model of TIMSS 2011 is currently under analysis.


Standard Error
Standard Error
0
0.161
0.322
0.484
0.645
−2
−1.5
−1
−0.5
0
0.5
1
Observed Outcome


Sampling Variance
Variance
0
0.104
0.208
0.312
0.416
−2
−1.5
−1
−0.5
0
0.5
1
Observed Outcome

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