

Not everyone's has the chance unequal access to open classroom discussion

Estimating unequal Access to school practices, when students are the informants of the practice of interest.

Advanced secondary analysis of ILSA: a discussion
of methods

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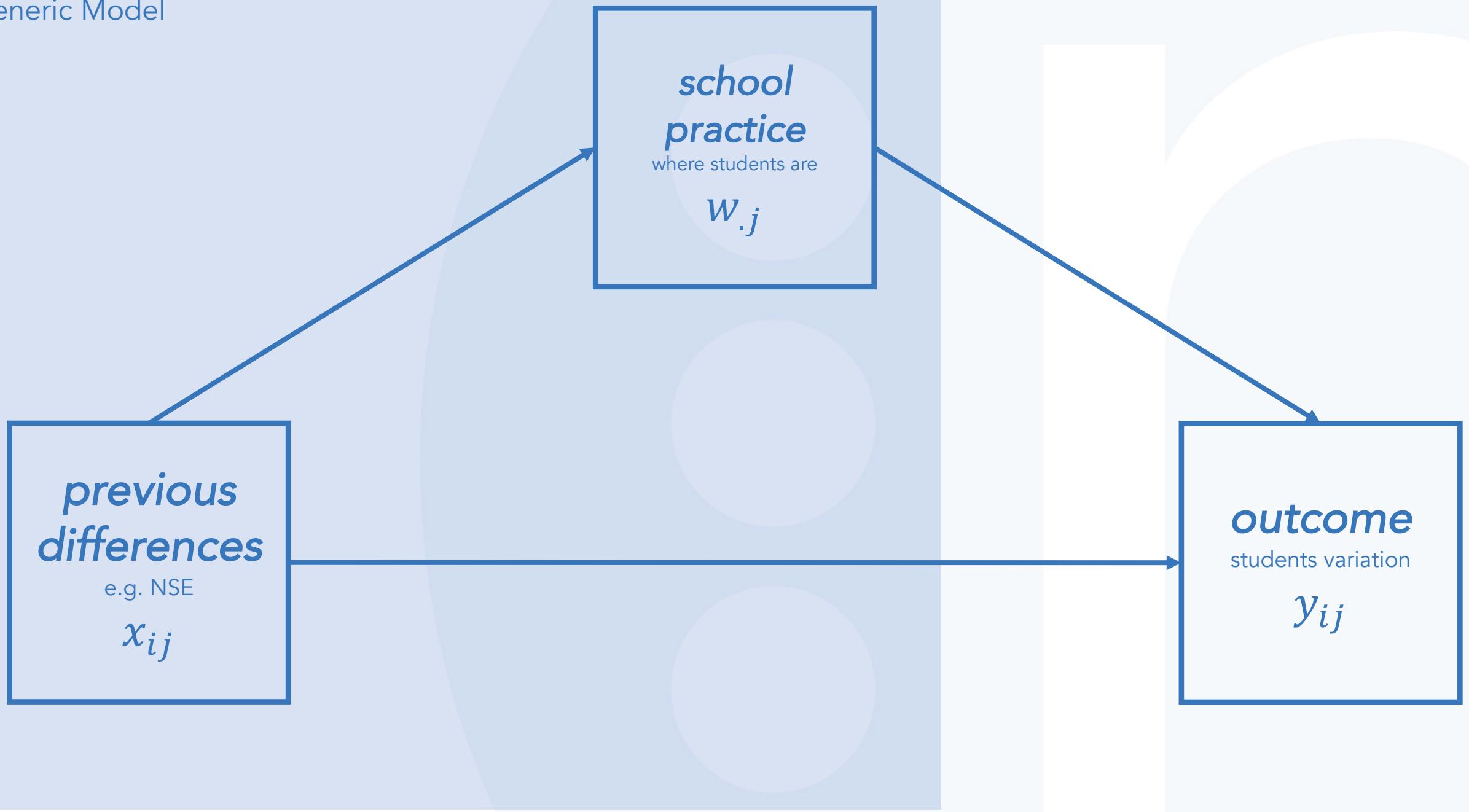
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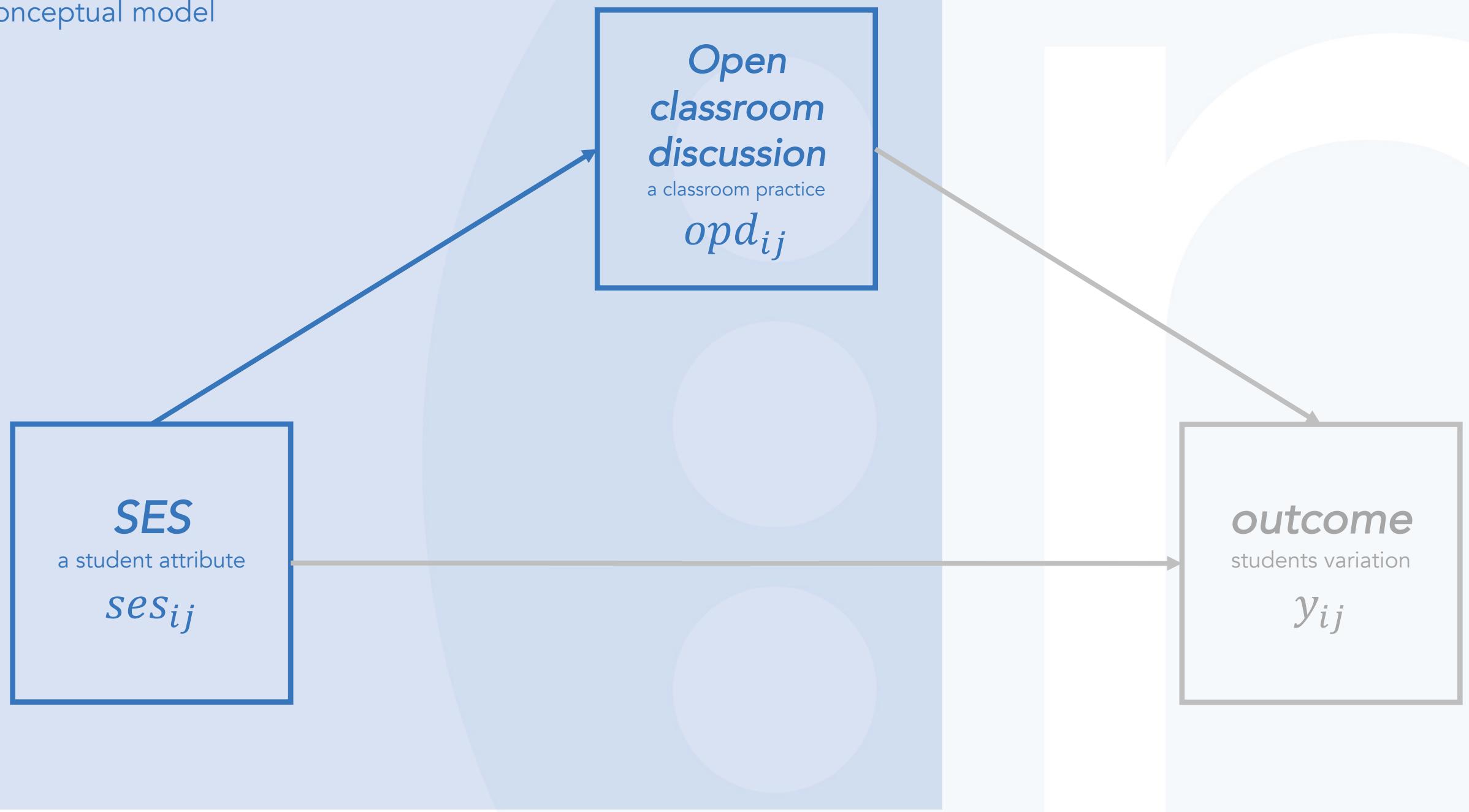
Unequal access to

Open classroom discussion

Opportunity learning gaps



Conceptual model



Open classroom discussion

- Classrooms where students are encouraged to **make up their minds**, discuss **different points of view** on political and social issues, guided by their teachers.
- Considered a **school effectiveness factor for the promotion of citizenry skills** (Almond & Verba, 1989; Hahn & Tocci, 1990).
- Is a classroom practice with **many positive returns** in civic and citizenship education
- **civic knowledge** (e.g., Isac, Maslowski, Creemers, & van der Werf, 2014)
- **political efficacy** (e.g., Knowles & McCafferty-Wright, 2015)
- **endorsement of egalitarian values** (e.g., Carrasco & Torres Irribarra, 2018)
- **voting intention** (e.g., Castillo, Miranda, Bonhomme, Cox, & Bascopé, 2014)
- **endorsement of authoritarianism (antidemocratic beliefs)** (e.g., Carrasco, Sandoval-Hernández, López, Maturana, forthcoming)
- **tolerance of corruption** (e.g., Carrasco & Pavón, forthcoming)

Unequal access

Learning opportunity gap

Unequal exposure to opportunities to learn
(Schmidt, et al 2001)

e.g., access to quality teachers is not equally distributed

(Akiba, LeTendre, & Scribner, 2007)

Disadvantaged students in the US have lesser access to **service learning** and to the exercise of **debates**, than the students from more affluent families

(Kahne & Middaugh, 2008)

Small positive relation between **student's SES** and **open classroom discussion** among British students

(Hoskin, Janmaat & Melis, 2017)

Unequal acces to

Open classroom discussion

How to estimate gaps in oportunities to learn

How to estimate open classroom discussion gaps?

Population average model or regression

What is the most likely relation among observations?

(e.g. Hoskin, Janmat & Melis, 2017)

$$opd_{ij} = \alpha + \delta_t ses_{ij} + \epsilon_{ij}$$

Within school model

How students perceive the attribute across schools?

(e.g. Castillo, et al, 2014)

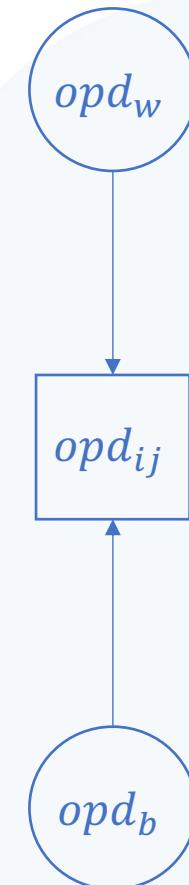
$$opd_{ij} = \alpha + \delta_w (ses_{ij} - \bar{ses}_{..}) + \dots + \theta_{.j} + \epsilon_{ij}$$

Between school model

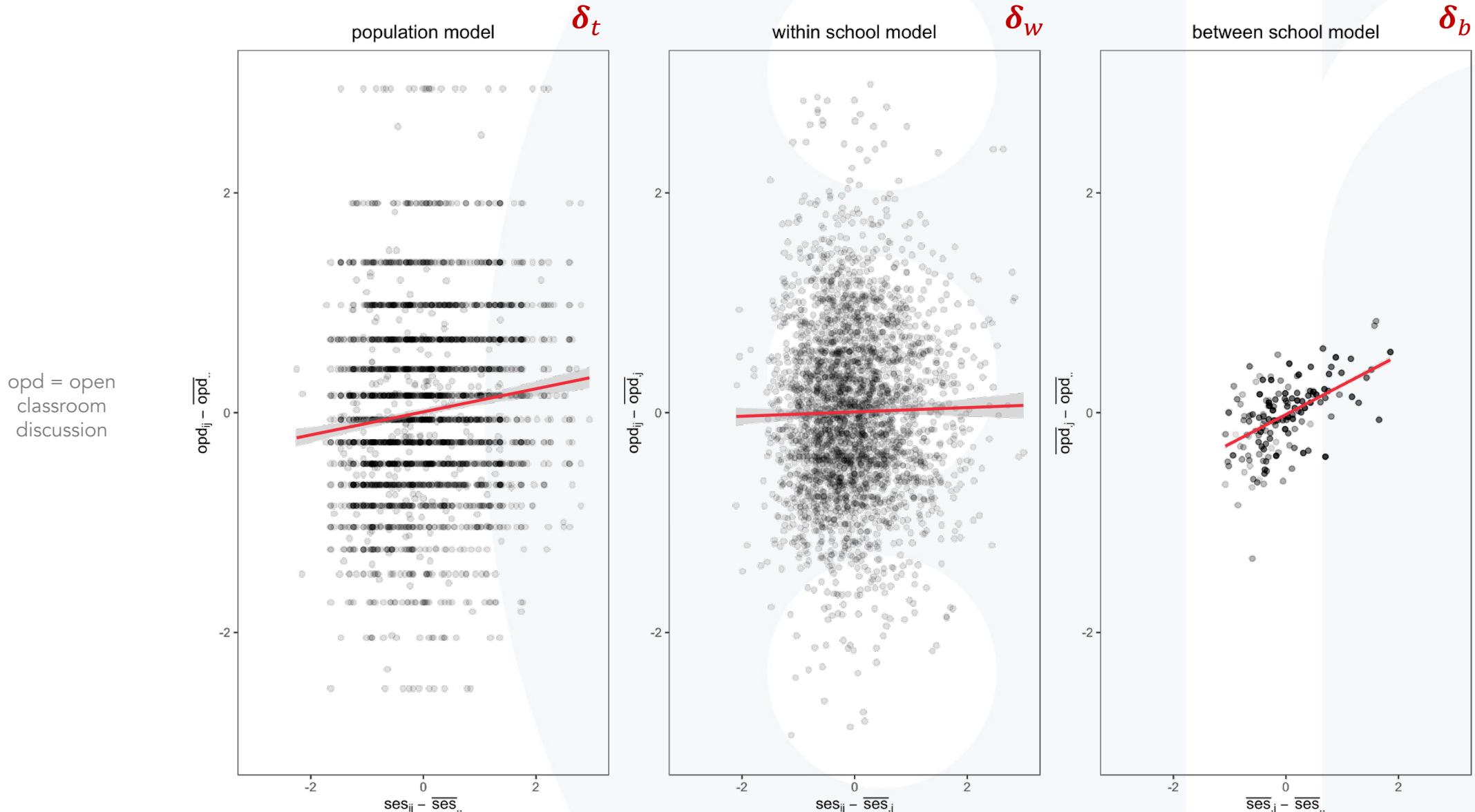
What is the most likely school they are attending to?

(e.g. Carrasco, Banerjee, Treviño, Villalobos, 2020)

$$opd_{ij} = \alpha + \delta_w (ses_{ij} - \bar{ses}_{.j}) + \delta_b (\bar{ses}_{.j} - \bar{ses}_{..}) + \theta_{.j} + \epsilon_{ij}$$



Different coefficients



Open classroom discussion

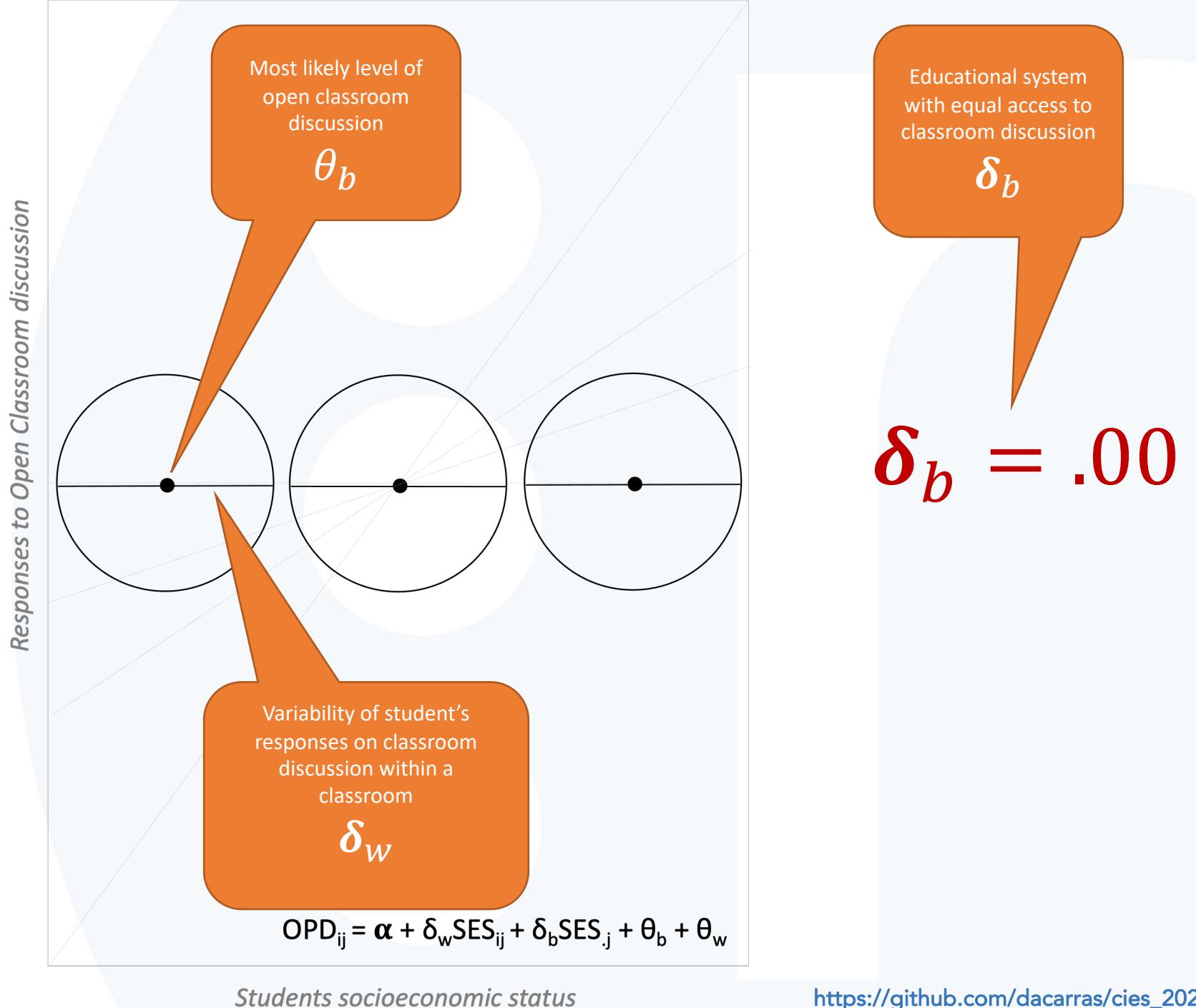
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Opportunities learning gaps

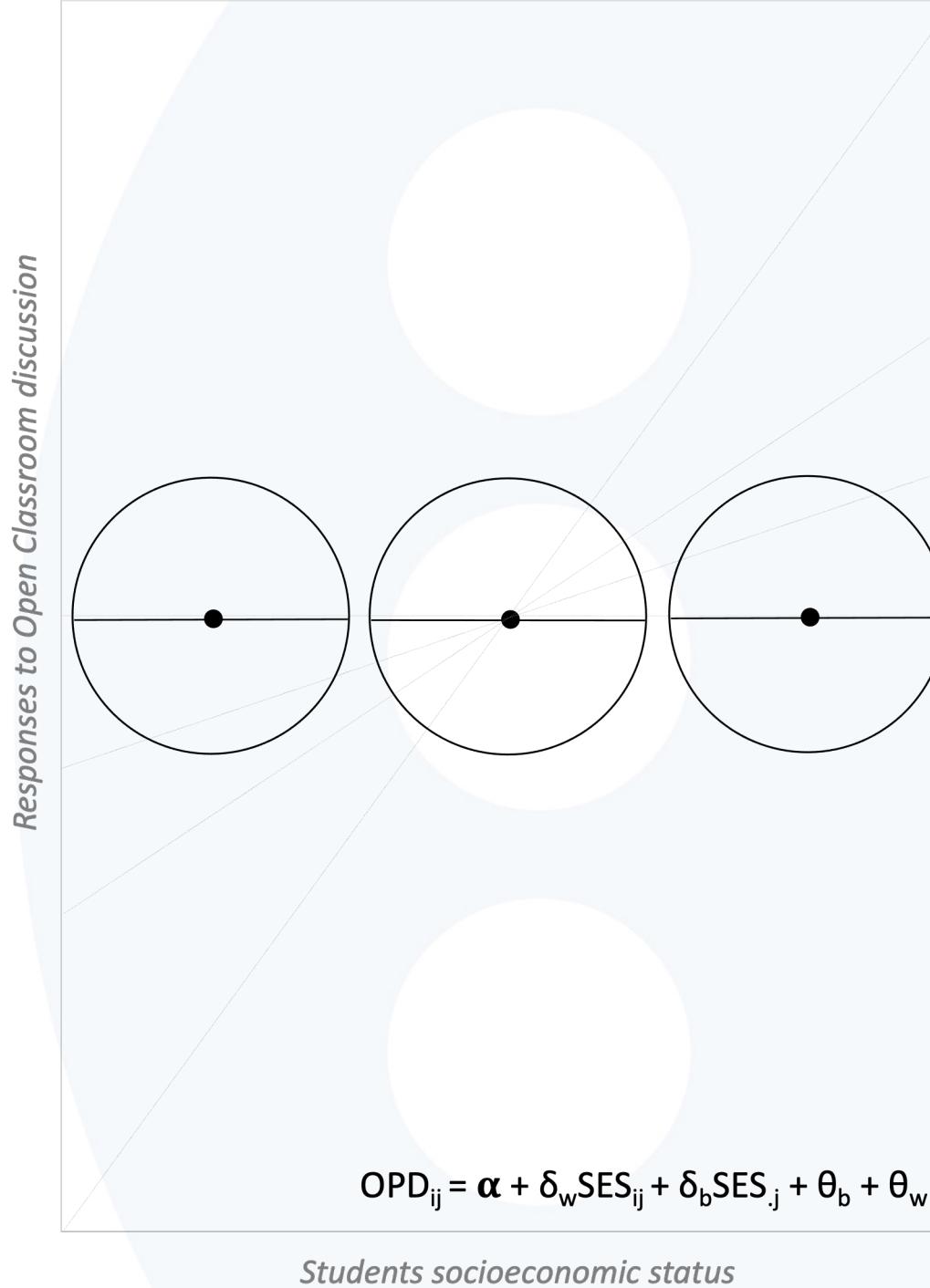
Coefficients representation

Geometric projection

Coefficient Representation



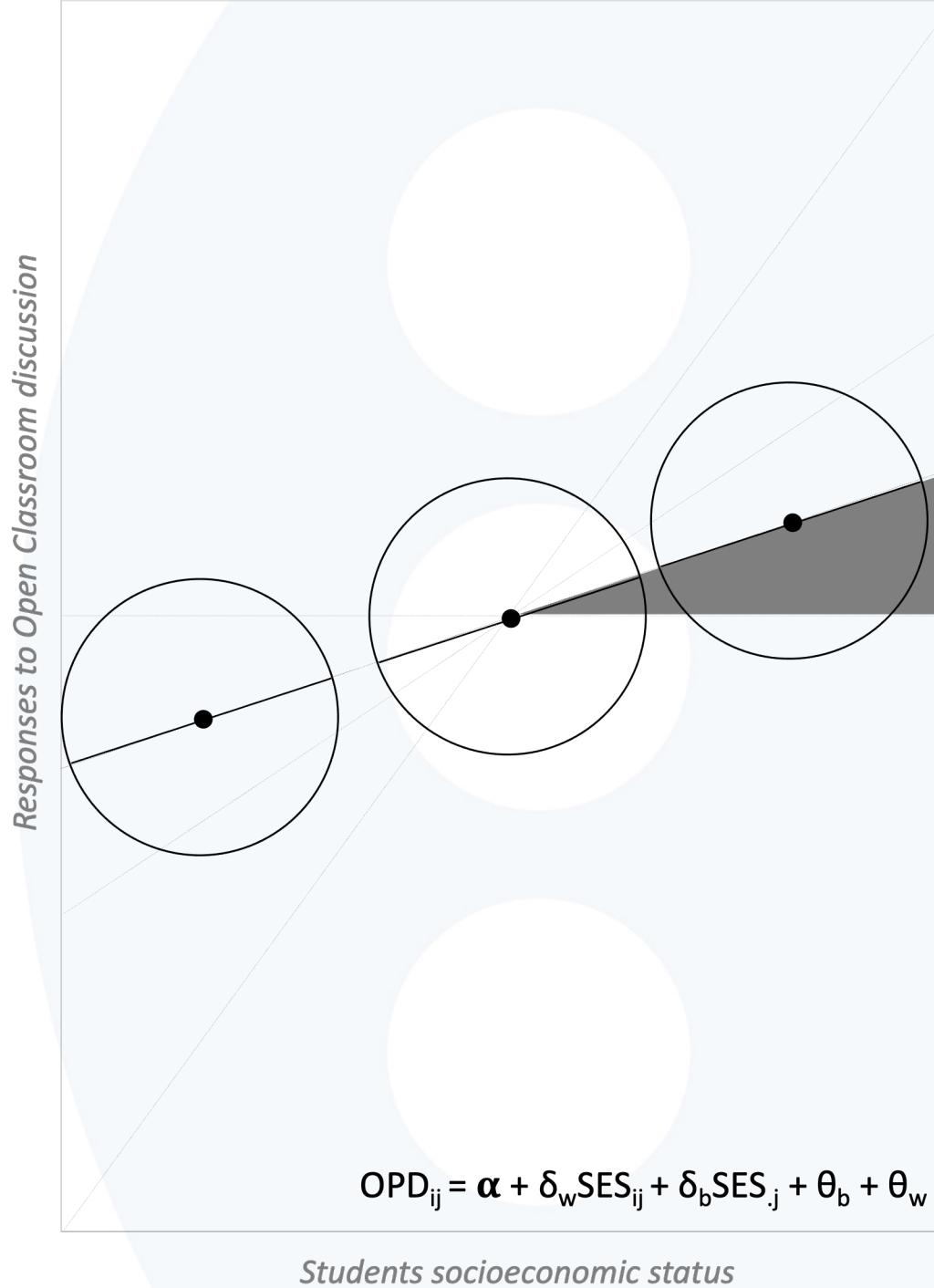
Coefficient Representation



$$\delta_b = .00$$

Access to the classroom is not conditioned by student's family SES

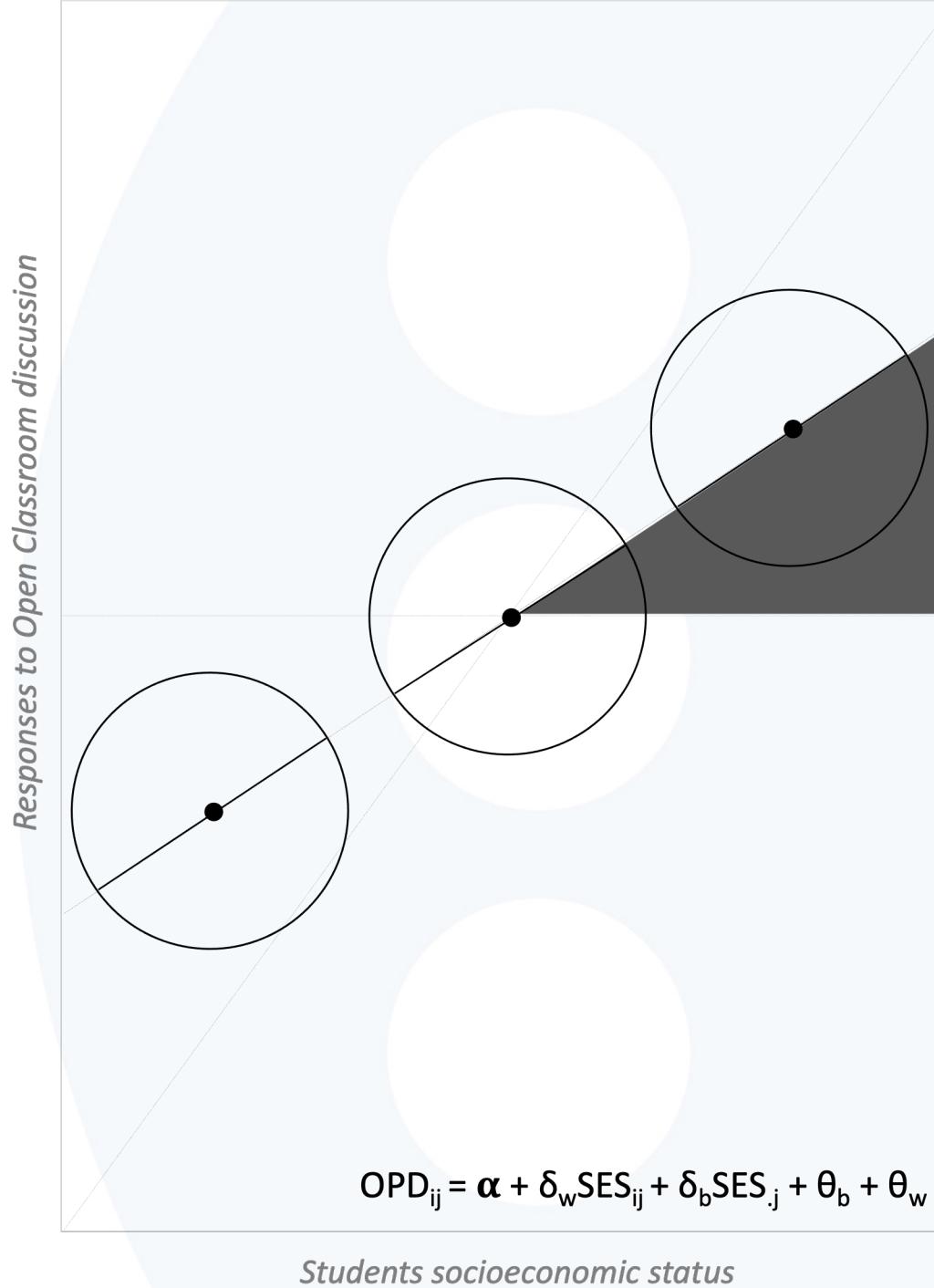
Coefficient Representation



$$\delta_b = .25$$

There is some noticeable gap

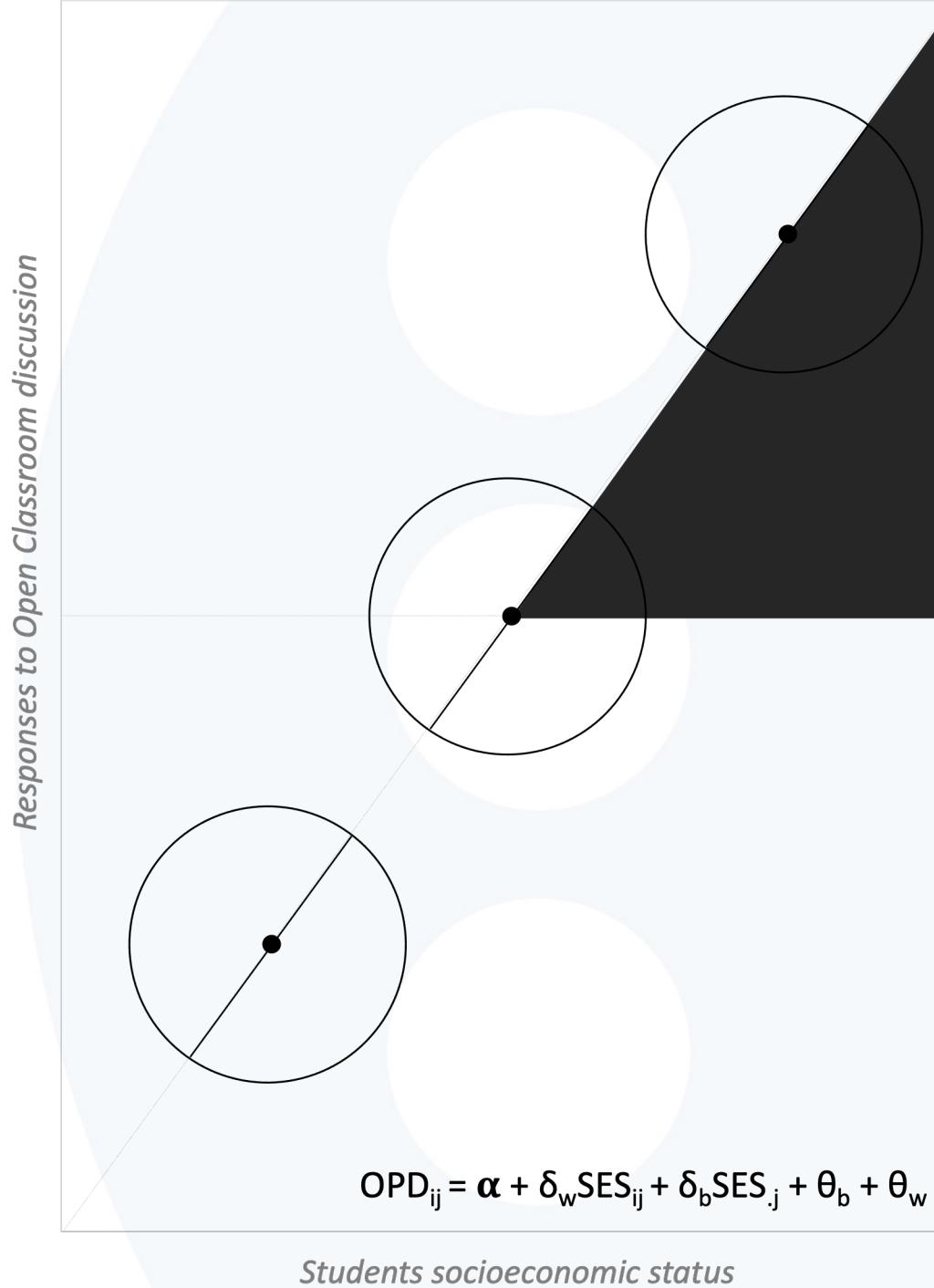
Coefficient Representation



$$\delta_b = .50$$

There is a large gap on access

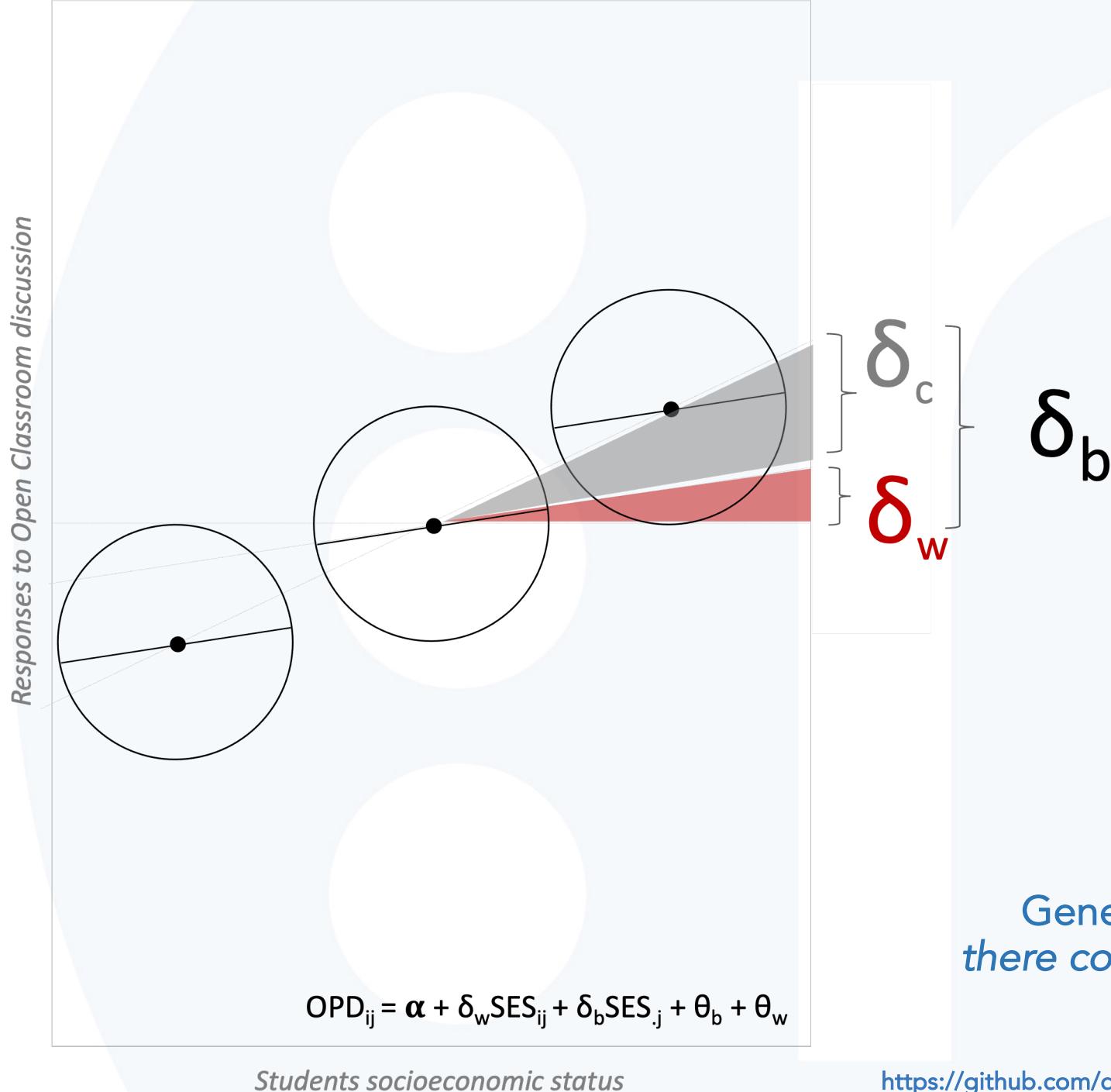
Coefficient Representation



$$\delta_b = 1.00$$

Access to the school practice is completely explained by students family's SES

Coefficient Representation



Opportunities learning gaps

Open classroom discussion gaps

Application

Method

- International Civic and Citizenship Education Study (2009 and 2016)
 - Random selection of schools of 8th graders
 - participation of intact classrooms
 - 150 schools and around 3000 to 5000 students per country
 - 38 countries and regions participated in 2009, and 24 countries and regions participated in 2016
- School practice (opd_ij)
 - Open classroom discussion (6 items)
 - “Teachers encourage students to express their opinions”
 - IRT WLE scores (M=50, SD=10), standardized using the international scale score (M=0, SD=1).
- Students Socioeconomic Status (ses_ij)
 - Books at home, parent’s education, and parent’s occupation
 - PCA scores (M=0, SD=1)

- Analytical strategy
 - Disaggregated model (Rights, et al. 2019)
 - SES is decomposed into SES_w and SES_b
 - We fit a single model per country, per year
 - $opd_{ij} = \alpha + \delta_w(ses_{ij} - \bar{ses}_{.j}) + \delta_b(\bar{ses}_{.j} - \bar{ses}_{..}) + \theta_{.j} + \epsilon_{ij}$
 - opd_{ij} scores are standardized using the international scale score. These are centered at zero, and have a standard deviation of 1, across all countries.
 - Pseudo Maximum Likelihood estimation with effective sample size weight scaling (Stapleton, 2013)
 - Models are fitted using Mplus via MplusAutomation package (Hallquist & Wiley, 2018)

Oportunities learning gaps

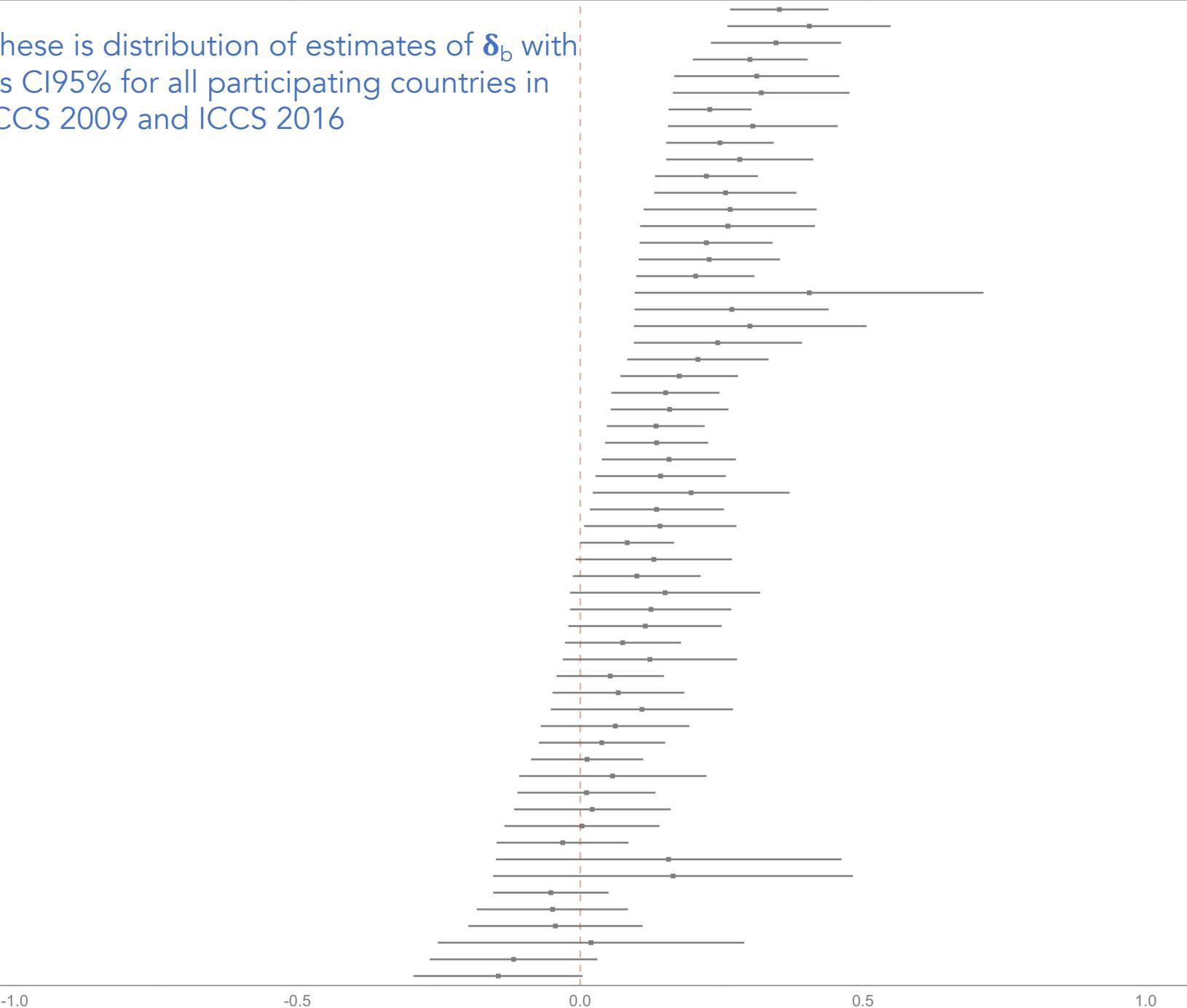
What results we got

Results

Results

PRY_09
DNK_16
NZL_09
IRL_09
ENG_09
COL_16
COL_09
SWE_09
NLD_16
MLT_16
GTM_09
SWE_16
DNW_16
EST_09
PER_16
BGR_16
TWN_09
NOR_09
DOM_16
DNK_09
BGR_09
DOM_09
TWN_16
CHL_09
FIN_16
CHL_16
ESP_09
POL_09
EST_16
HKG_09
AUT_09
ITA_16
MEX_16
THA_09
CZE_09
NLD_09
FIN_09
IDN_09
HRV_16
HKG_16
SVK_09
MEX_09
BFL_16
LIE_09
GRC_09
ITA_09
SVN_09
KOR_09
SVN_16
CYP_09
BFL_09
KOR_16
NOR_16
LVA_16
LVA_09
RUS_16
RUS_09
LTU_16
CHE_09

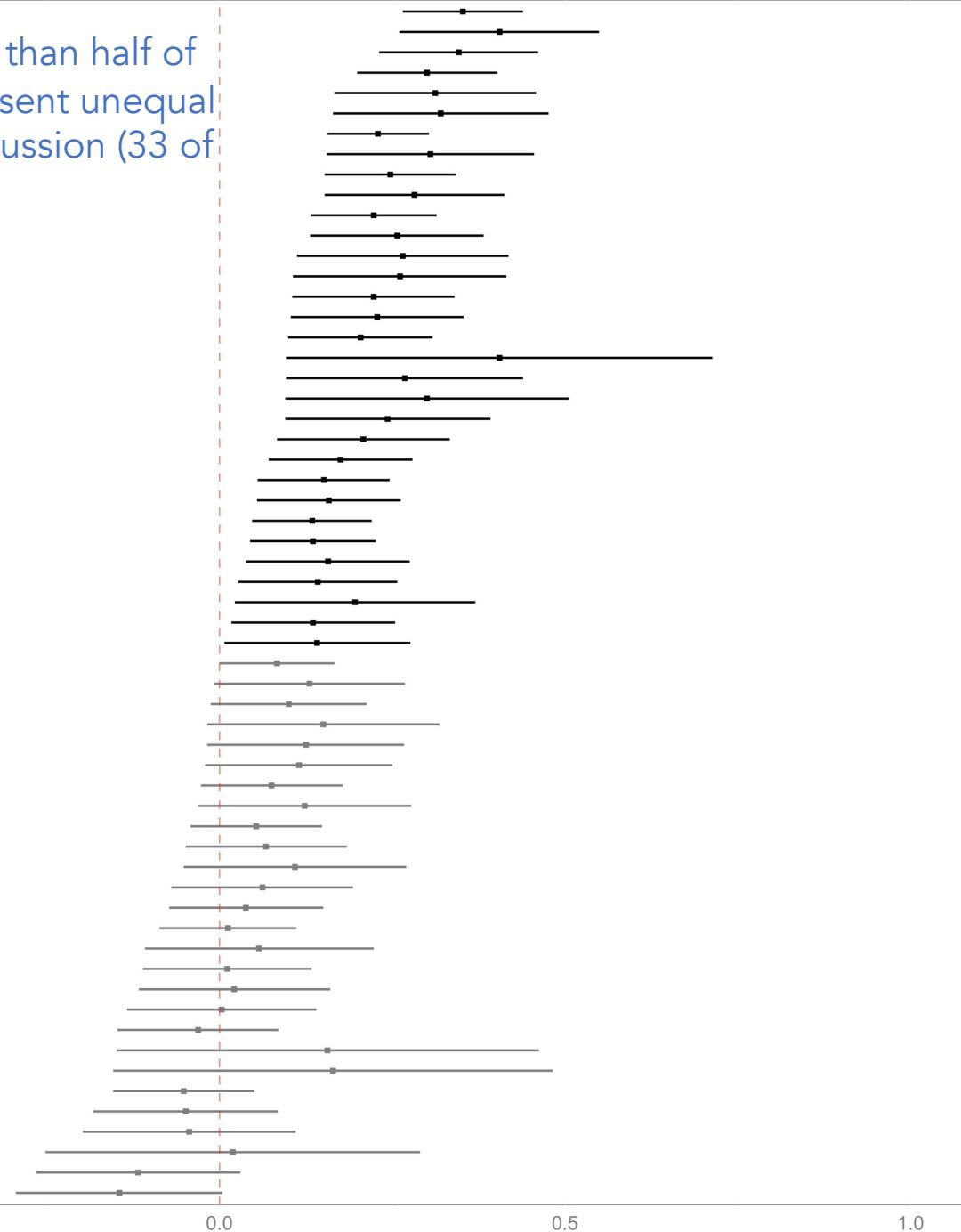
These is distribution of estimates of δ_b with its CI95% for all participating countries in ICCS 2009 and ICCS 2016



Results

PRY_09
DNK_16
NZL_09
IRL_09
ENG_09
COL_16
COL_09
SWE_09
NLD_16
MLT_16
GTM_09
SWE_16
DNW_16
EST_09
PER_16
BGR_16
TWN_09
NOR_09
DOM_16
DNK_09
BGR_09
DOM_09
TWN_16
CHL_09
FIN_16
CHL_16
ESP_09
POL_09
EST_16
HKG_09
AUT_09
ITA_16
MEX_16
THA_09
CZE_09
NLD_09
FIN_09
IDN_09
HRV_16
HKG_16
SVK_09
MEX_09
BFL_16
LIE_09
GRC_09
ITA_09
SVN_09
KOR_09
SVN_16
CYP_09
BFL_09
KOR_16
NOR_16
LVA_16
LVA_09
RUS_16
RUS_09
LTU_16
CHE_09

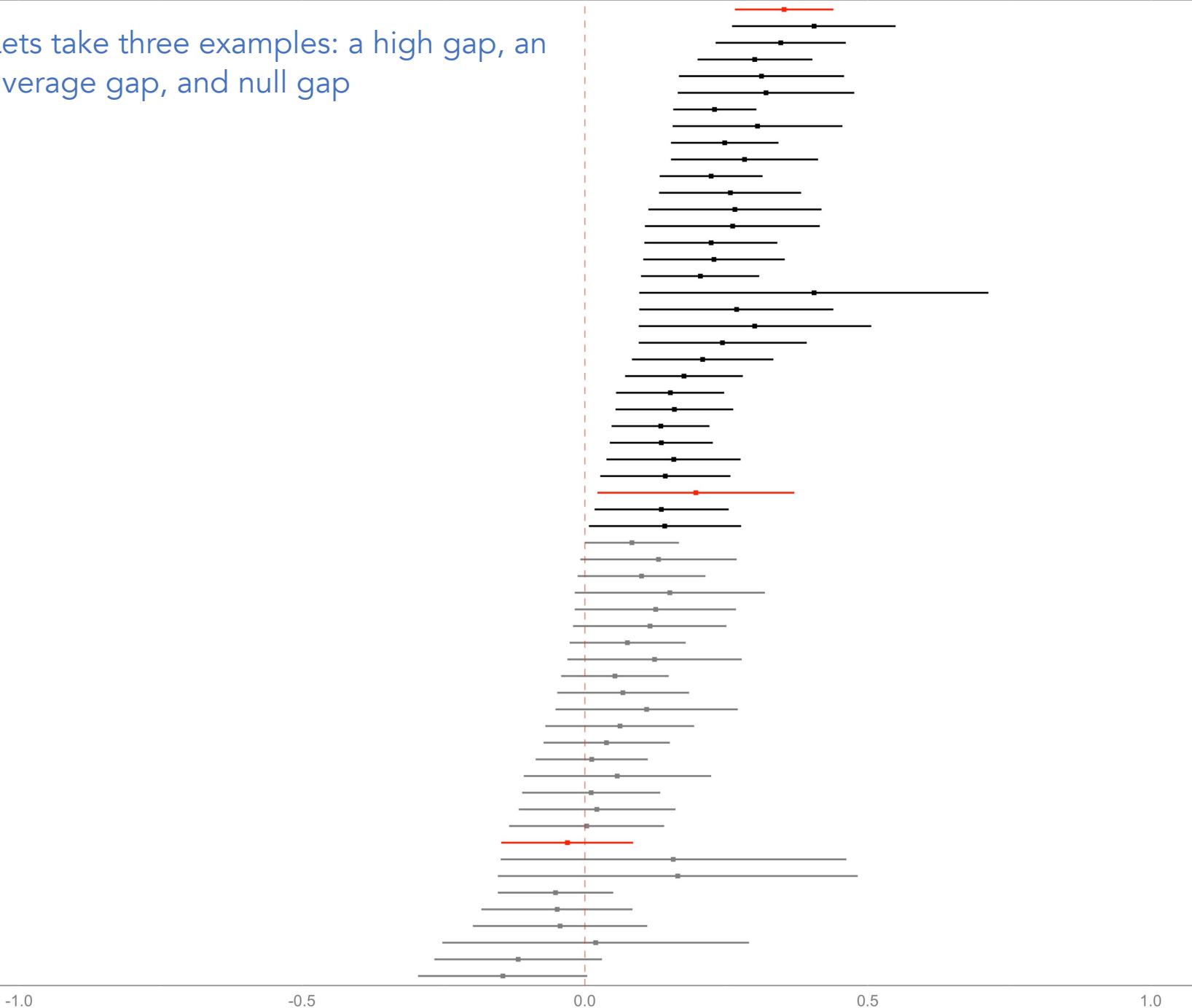
Among all participating, more than half of the participating countries present unequal access to open classroom discussion (33 of 59)



Results

PRY_09
DNK_16
NZL_09
IRL_09
ENG_09
COL_16
COL_09
SWE_09
NLD_16
MLT_16
GTM_09
SWE_16
DNW_16
EST_09
PER_16
BGR_16
TWN_09
NOR_09
DOM_16
DNK_09
BGR_09
DOM_09
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CHL_09
FIN_16
CHL_16
ESP_09
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HKG_09
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ITA_16
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NLD_09
FIN_09
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BFL_16
LIE_09
GRC_09
ITA_09
SVN_09
KOR_09
SVN_16
CYP_09
BFL_09
KOR_16
NOR_16
LVA_16
LVA_09
RUS_16
RUS_09
LTU_16
CHE_09

Lets take three examples: a high gap, an average gap, and null gap



Paraguay ICCS 2009

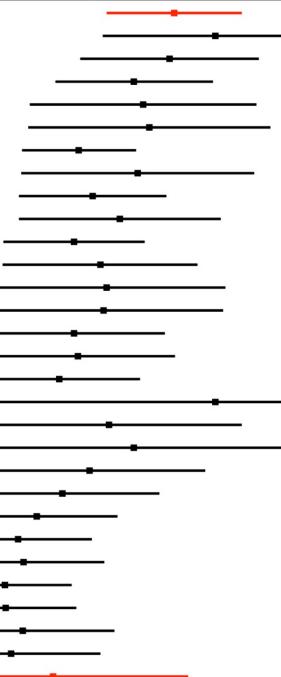
$\delta_b = .35$ CI95%[.26, .44]

PRY_09

DNK_16
NZL_09
IRL_09
ENG_09
COL_16
COL_09
SWE_09
NLD_16

MLT_16
GTM_09
SWE_16
DNW_16
EST_09
PER_16
BGR_16
TWN_09
NOR_09
DOM_16
DNK_09
BGR_09
DOM_09
TWN_16
CHL_09
FIN_16
CHL_16
ESP_09
POL_09
EST_16
HKG_09

Highest
gap !



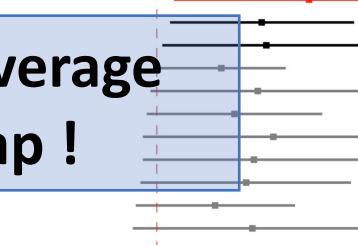
Hong Kong ICCS 2009

$\delta_b = .20$ CI95%[.02, .37]

AUT_09
ITA_16
MEX_16
THA_09
CZE_09
NLD_09
FIN_09
IDN_09

HRV_16
HKG_16
SVK_09
MEX_09
BFL_16
LIE_09
GRC_09
ITA_09
SVN_09
KOR_09
SVN_16
CYP_09
BFL_09

Average
gap !

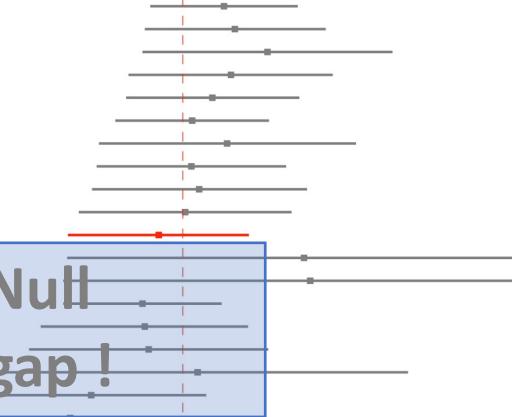


Belgium (Flemish) ICCS 2009

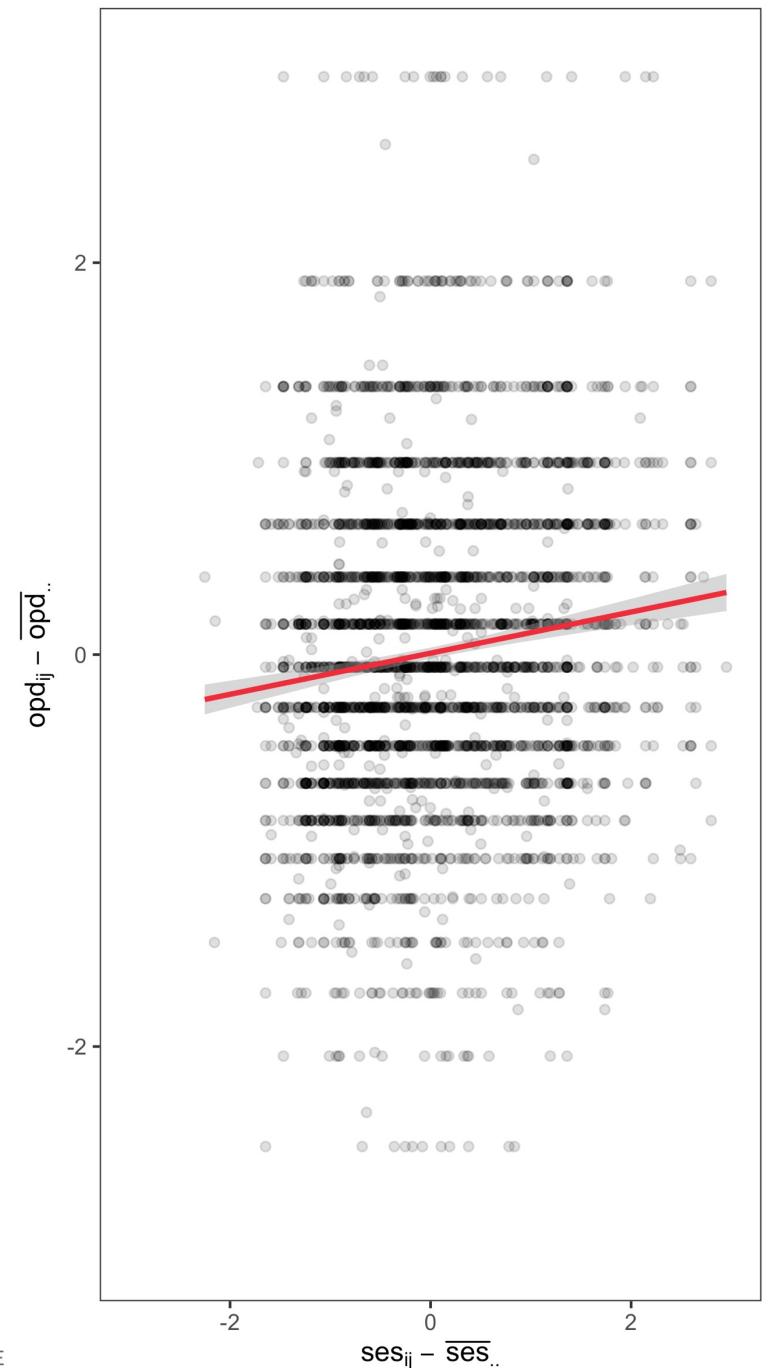
$\delta_b = -.03$ CI95%[-0.15, .09]

KOR_16
NOR_16
LVA_16
LVA_09
RUS_16
RUS_09
LTU_16
CHE_09

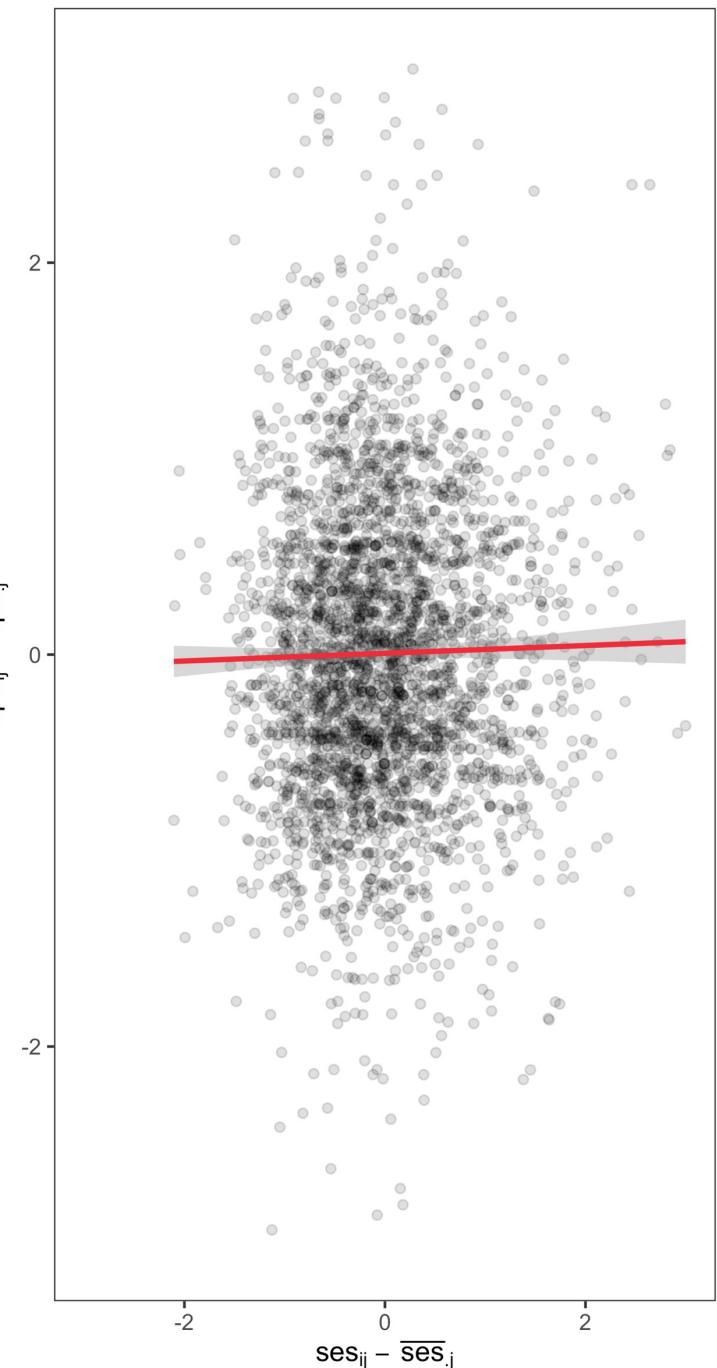
Null
gap !



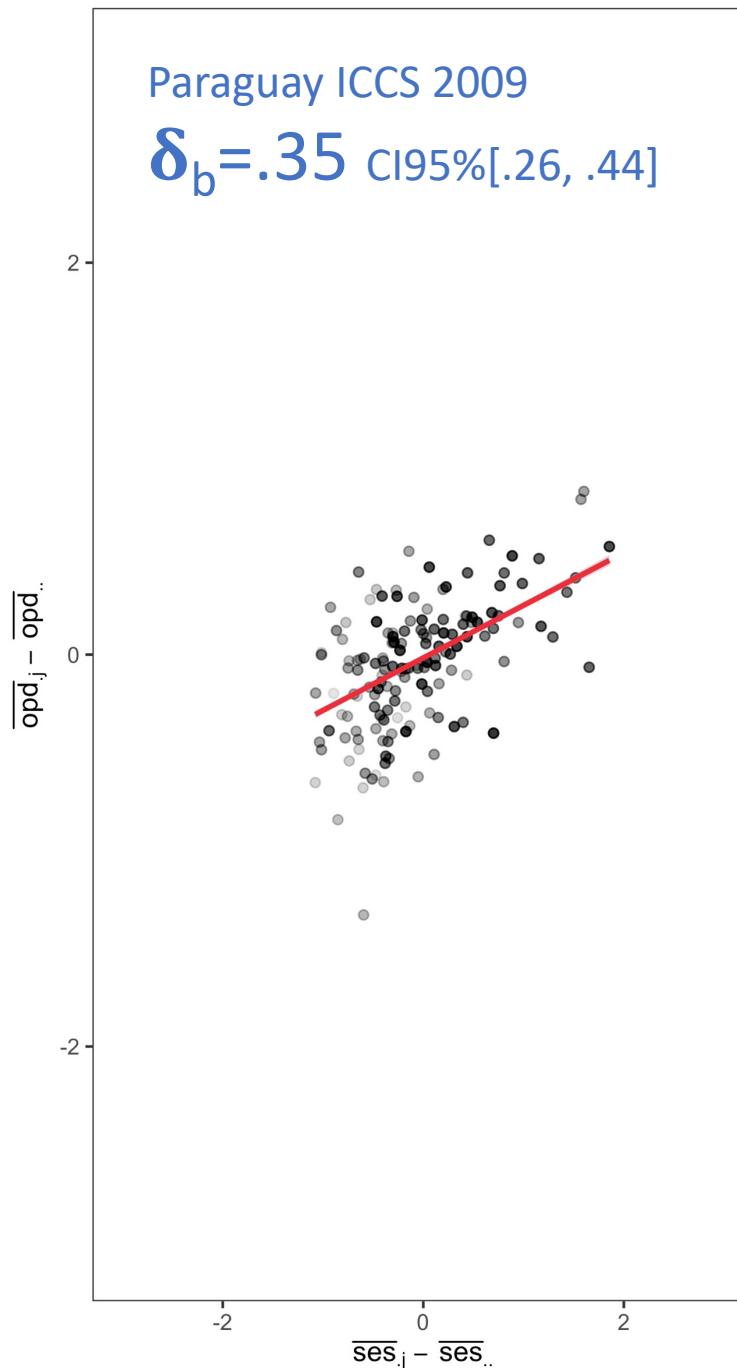
population model



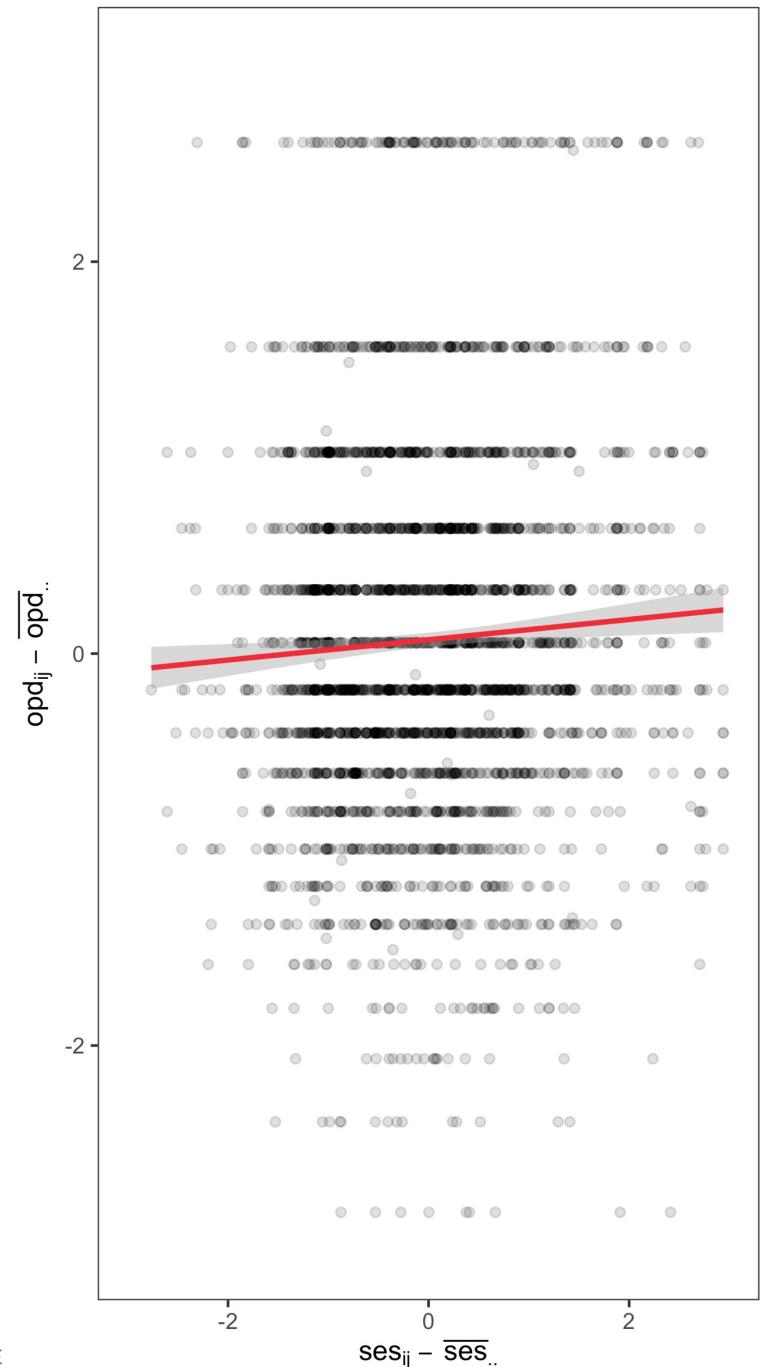
within school model



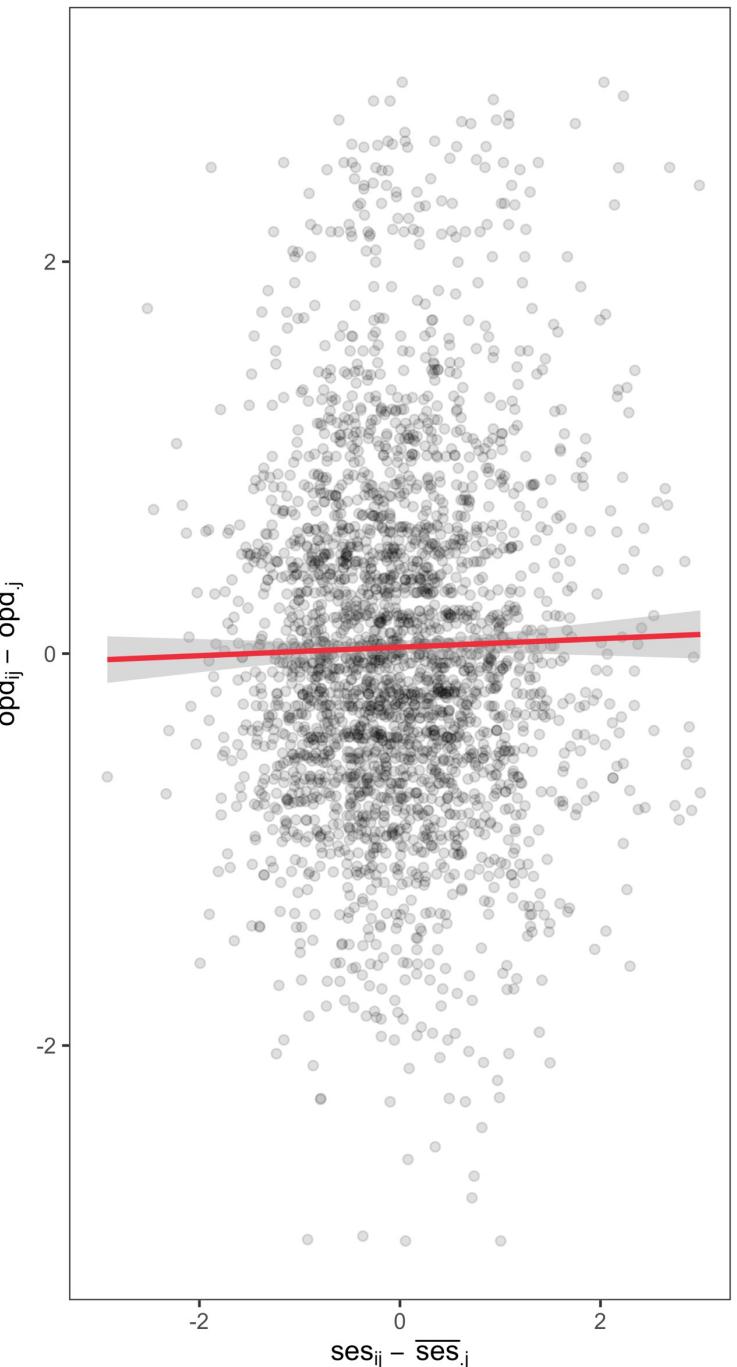
between school model



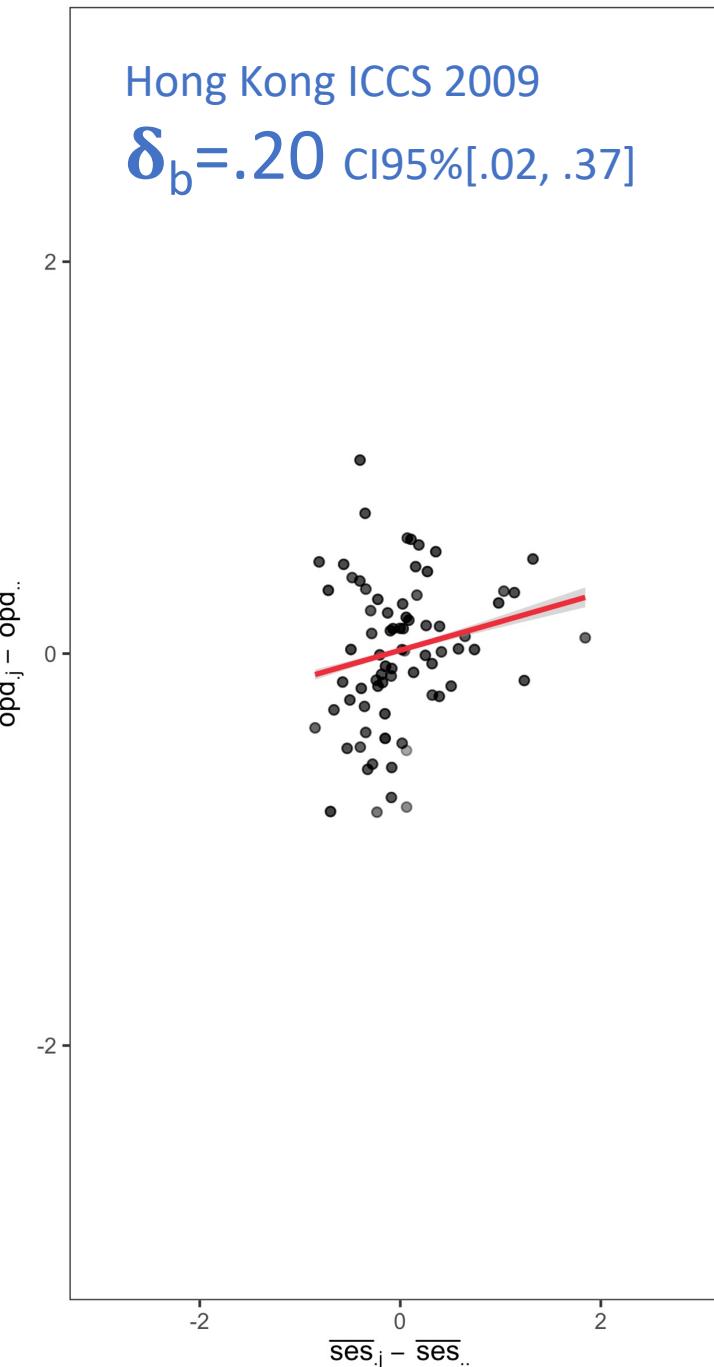
population model



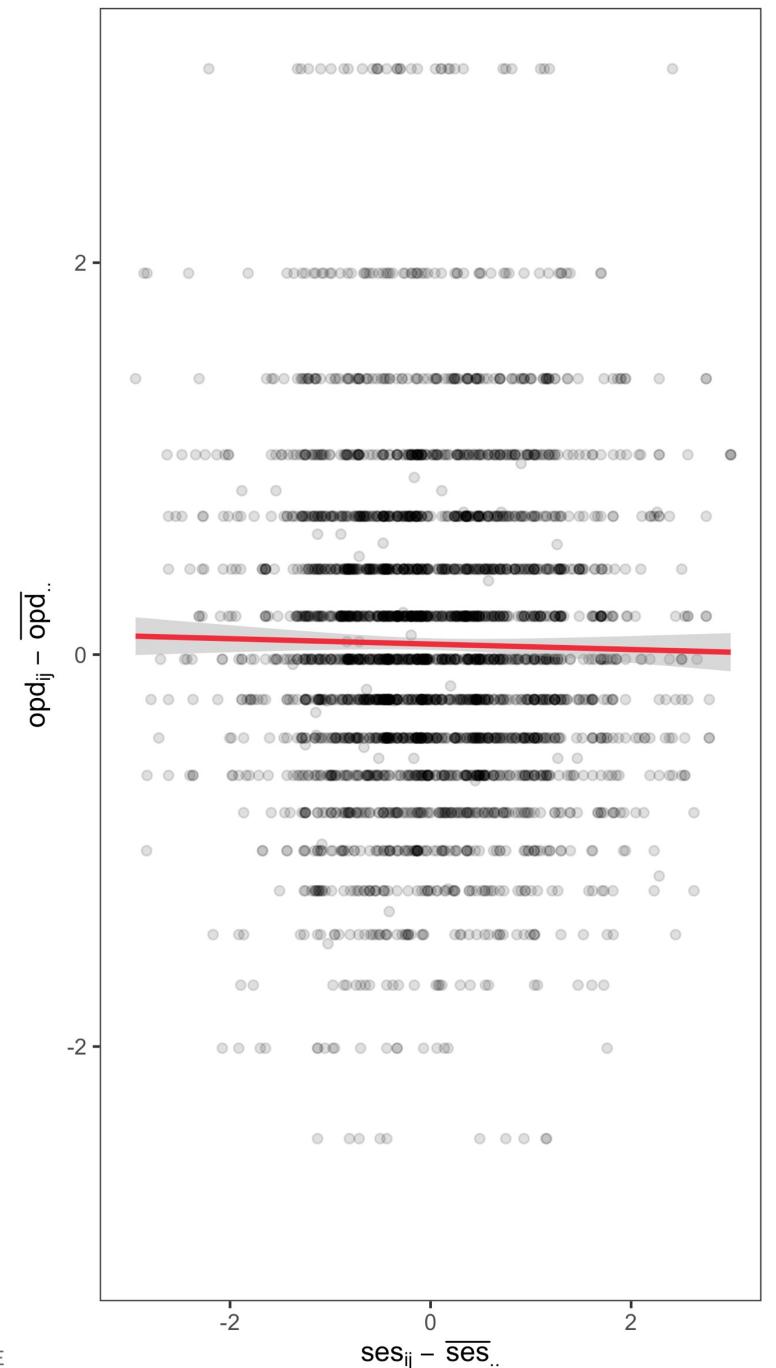
within school model



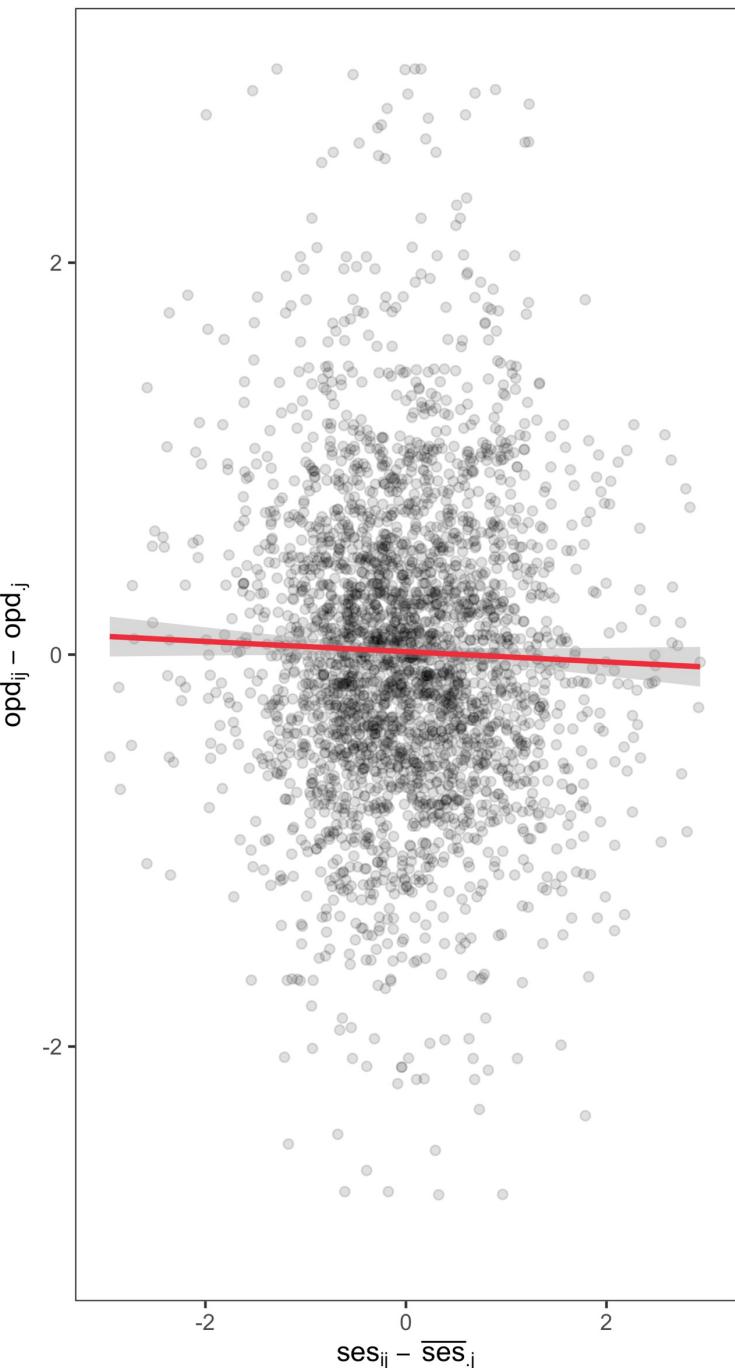
between school model



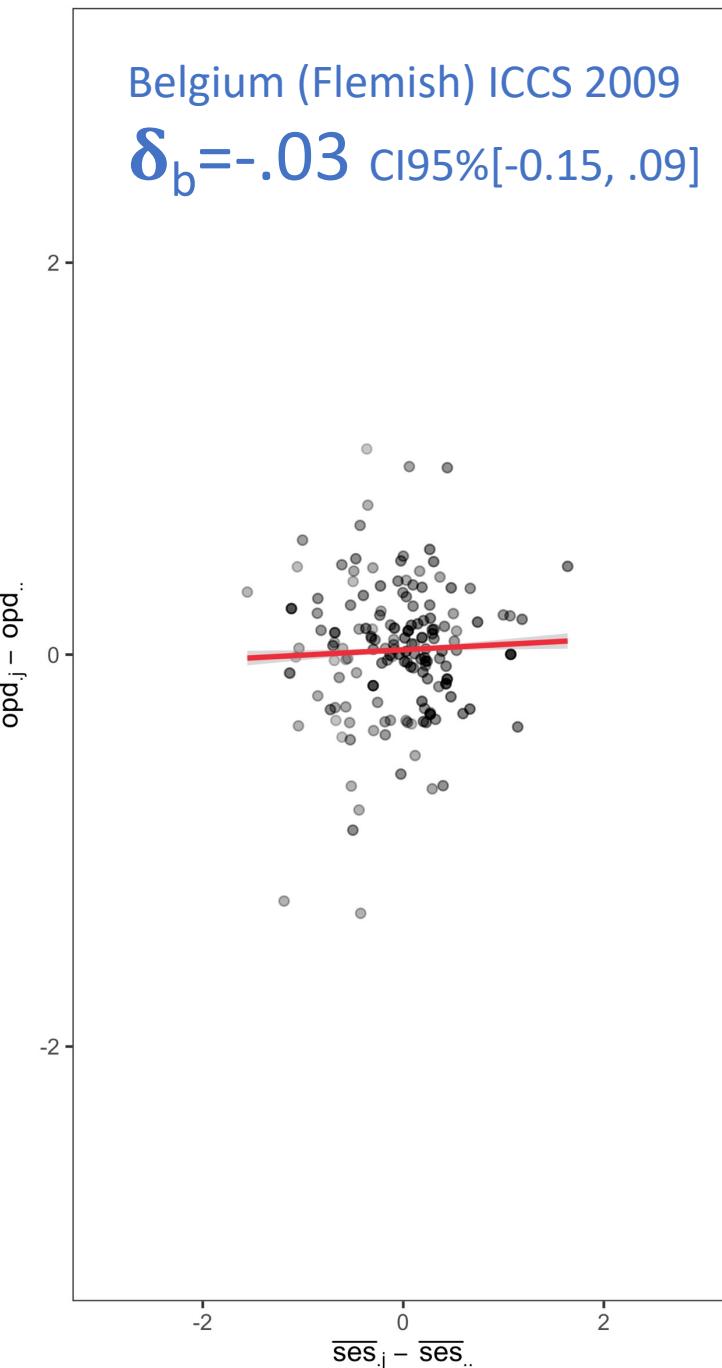
population model



within school model



between school model



Oportunities learning gaps

What was our workflow

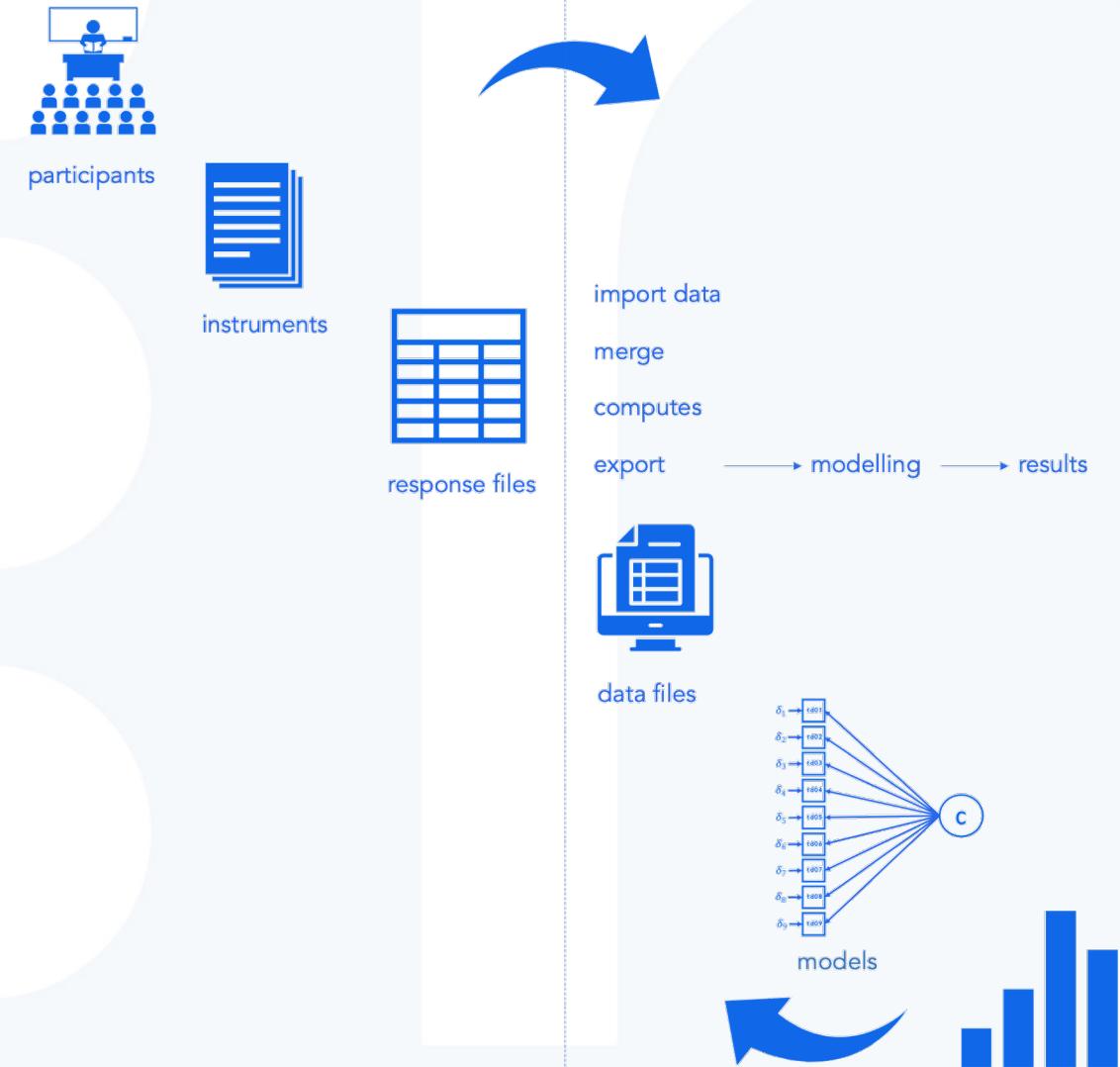
How to replicate the current results

https://github.com/dacarras/cies_2021_opd

Data Analysis workflow

https://github.com/dacarras/cies_2021_opd

- Data Importation
 - Original files turn into manageable files
 - Many files into single files
- Data preparation
 - Computes
 - Recodes
 - Scale
- Fit Models
 - Specify model
 - Fit as many models are needed
- Process estimates
 - Parse output into readable objects
- Summarize results
 - Tables
 - Figure



Data Analysis workflow

- Data Importation
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01_import_data.rmd

02_prepare_data.rmd

03_fit_models.rmd

04_get_estimates.rmd

05_descriptives_plots.rmd

01_import_data.rmd

```
165
166 # -----
167 # import all data
168 # -----
169
170 # -----
171 # get list of files
172 # -----
173
174 iccs_2009_files <- paste0(data_folder, list.files(path = data_folder, pattern = "C2.*"))
175 iccs_2016_files <- paste0(data_folder, list.files(path = data_folder, pattern = "C3.*"))
176
177 # -----
178 # import all and merge
179 # -----
180
181 library(dplyr)
182 iccs_2009 <- iccs_2009_files %>%
183     purrr::map_df(haven::read_sav)
184
185 library(dplyr)
186 iccs_2016 <- iccs_2016_files %>%
187     purrr::map_df(haven::read_sav)
188
```

02_prepare_data.rmd

```
175  
176 data_09 <- readRDS(paste0(data_folder, 'iccs_2009_stu_int.rds'))  
177  
178 # -----  
179 # generic survey design variables  
180 # -----  
181  
182 library(dplyr)  
183 data_model_09 <- data_09 %>%  
184     # remove labels  
185     r4sda::remove_labels() %>%  
186     # clustering  
187     mutate(id_i = seq(1:nrow(.)) ) %>%  
188     mutate(id_j = as.numeric(as.factor(paste0(COUNTRY, JKZONES, IDSCHOOL)))) %>%  
189     mutate(id_s = as.numeric(as.factor(paste0(COUNTRY, JKZONES)))) %>%  
190     mutate(id_r = as.numeric(as.factor(paste0(COUNTRY, JKZONES, JKREPS)))) %>%  
191     mutate(id_k = as.numeric(as.factor(paste0(COUNTRY)))) %>%  
192     # survey weights  
193     mutate(wt = TOTWGTS) %>%  
194     # students weights  
195     mutate(wi = WGTFACT2S*WGTADJ2S*WGTADJ3S) %>%  
196     # school weights  
197     mutate(wj = WGTFACT1*WGTADJ1S) %>%  
198     # create senate weights  
199     r4sda::senate_weights(., wt = 'wt', id_k = 'id_k', scale = 1000) %>%  
200     # create scaled weights  
201     r4sda::lsa_weights(.,  
202         id_i = 'id_i',  
203         id_j = 'id_j',  
204         id_k = 'id_k',  
205         wt = 'wt',  
206         wi = 'wi',  
207         wj = 'wj') %>%  
208     dplyr::glimpse()
```

The present code generate clustering variables to aid the use of the sampling design.

It also generate survey weights with friendlier names, it scale weights for population and for mixed models.

03_fit_models.rmd

```
310 library(MplusAutomation)
311 opportunity_gap_model <- mplusObject(
312   MODEL =
313   %WITHIN%
314   opd on ses_w (w);
315
316
317
318 %BETWEEN%
319 opd on ses_b (b);
320
321 ',
322 ANALYSIS =
323 TYPE = TWOLEVEL COMPLEX;
324 ESTIMATOR = MLR;
325 ',
326
327 VARIABLE =
328 ! variables with restricted variance
329 WITHIN = ses_w;
330 BETWEEN = ses_b;
331
332 !complex sample design
333 STRATIFICATION = id_s;
334 CLUSTER = id_j;
335
336 !multilevel specification
337 WEIGHT = wi;
338 BWEIGHT = wj;
339 WTSCALE = ECLUSTER;
340 BWTSCALE = SAMPLE;
341
342 USEVARIABLES =
343 opd
344 ses_w
345 ses_b
346 ;
347 ',
348 MODELCONSTRAINT =
349 '
350 new (
351 ce_w
352 ce_b
353 ce_c
354 );
355
356 !contextual effect of ses
357 ce_w = w;
358 ce_b = b;
359 ce_c = b - w;
360 ',
361 OUTPUT =
362 STAND
363 TECH1
364 TECH3
365 SAMPSTAT
366 CINTERVAL
367 ;
368 ',
369 rdata = opd_09_CHL)
370
371
```

```
453 # -----
454 # fit models
455 # -----
456
457 fit_09_AUT <- mplusModeler(gap_09_AUT, modelout = 'fit_09_AUT.inp', run = 1L, hashfilename = FALSE)
458 fit_09_BGR <- mplusModeler(gap_09_BGR, modelout = 'fit_09_BGR.inp', run = 1L, hashfilename = FALSE)
459 fit_09_CHL <- mplusModeler(gap_09_CHL, modelout = 'fit_09_CHL.inp', run = 1L, hashfilename = FALSE)
460 fit_09_TWN <- mplusModeler(gap_09_TWN, modelout = 'fit_09_TWN.inp', run = 1L, hashfilename = FALSE)
461 fit_09_COL <- mplusModeler(gap_09_COL, modelout = 'fit_09_COL.inp', run = 1L, hashfilename = FALSE)
462 fit_09_CYP <- mplusModeler(gap_09_CYP, modelout = 'fit_09_CYP.inp', run = 1L, hashfilename = FALSE)
463 fit_09_CZE <- mplusModeler(gap_09_CZE, modelout = 'fit_09_CZE.inp', run = 1L, hashfilename = FALSE)
464 fit_09_DNK <- mplusModeler(gap_09_DNK, modelout = 'fit_09_DNK.inp', run = 1L, hashfilename = FALSE)
465 fit_09_DOM <- mplusModeler(gap_09_DOM, modelout = 'fit_09_DOM.inp', run = 1L, hashfilename = FALSE)
466 fit_09_EST <- mplusModeler(gap_09_EST, modelout = 'fit_09_EST.inp', run = 1L, hashfilename = FALSE)
467 fit_09_FIN <- mplusModeler(gap_09_FIN, modelout = 'fit_09_FIN.inp', run = 1L, hashfilename = FALSE)
468 fit_09_GRC <- mplusModeler(gap_09_GRC, modelout = 'fit_09_GRC.inp', run = 1L, hashfilename = FALSE)
469 fit_09_GTM <- mplusModeler(gap_09_GTM, modelout = 'fit_09_GTM.inp', run = 1L, hashfilename = FALSE)
470 fit_09_HKG <- mplusModeler(gap_09_HKG, modelout = 'fit_09_HKG.inp', run = 1L, hashfilename = FALSE)
471 fit_09_IDN <- mplusModeler(gap_09_IDN, modelout = 'fit_09_IDN.inp', run = 1L, hashfilename = FALSE)
472 fit_09_IRL <- mplusModeler(gap_09_IRL, modelout = 'fit_09_IRL.inp', run = 1L, hashfilename = FALSE)
473 fit_09_ITA <- mplusModeler(gap_09_ITA, modelout = 'fit_09_ITA.inp', run = 1L, hashfilename = FALSE)
474 fit_09_KOR <- mplusModeler(gap_09_KOR, modelout = 'fit_09_KOR.inp', run = 1L, hashfilename = FALSE)
475 fit_09_LVA <- mplusModeler(gap_09_LVA, modelout = 'fit_09_LVA.inp', run = 1L, hashfilename = FALSE)
476 fit_09_LIE <- mplusModeler(gap_09_LIE, modelout = 'fit_09_LIE.inp', run = 1L, hashfilename = FALSE)
```

We specify the model once.

Then this model is manipulated as an object and helps to fit the same model onto each country data

04_get_estimates.rmd

```

125 # read all
126 model_estimates <- MplusAutomation::readModels(target = paste0(syntax_folder))
127
128 # there should be 59 estimates models
129 length(model_estimates)
130
131 ...
132
133 ## Standardized
134
135 ```{r, echo=TRUE}
136
137 #-----
138 # extract estimates
139 #-----
140
141 #-----
142 # pseudo function to get estimates
143 #-----
144
145 get_est <- function(model_estimates, object) {
146
147   require(dplyr)
148
149   numeric <- object
150
151   estimates <- model_estimates[[numeric]]$parameters$unstandardized %>%
152     dplyr::filter(param == 'SES_B') %>%
153     mutate(star = case_when(
154       pval < .001 ~ '***',
155       pval < .01 ~ '**',
156       pval < .05 ~ '*',
157       pval >= .05 ~ '')) %>%
158     mutate(dep = stringr::str_remove(paramHeader, '.ON')) %>%
159     mutate(cov = param) %>%
160     mutate(file = model_estimates[[numeric]]$summaries$filename) %>%
161     dplyr::select(dep, cov, est, se, pval, star, file)
162
163 ci_level <- model_estimates[[numeric]]$parameters$ci.unstandardized %>%
164   dplyr::filter(param == 'SES_B') %>%
165   mutate(level = BetweenWithin) %>%
166   mutate(ll = low2.5) %>%
167   mutate(ul = up2.5) %>%
168   mutate(dep = stringr::str_remove(paramHeader, '.ON')) %>%
169   mutate(cov = param) %>%
170   dplyr::select(cov, ll, ul)
171
172 table <- dplyr:::left_join(estimates, ci_level, by = 'cov') %>%
173   mutate(ctry = stringr::str_remove(file, '.out')) %>%
174   mutate(ctry = stringr::str_remove(ctry, 'fit_09_')) %>%
175   mutate(ctry = stringr::str_remove(ctry, 'fit_16_')) %>%
176   mutate(year = dplyr:::if_else(stringr::str_detect(file, '16'), '16', '09')) %>%
177   dplyr:::select(file, ctry, year, dep, cov, est, se, pval, star, ll, ul)
178
179 return(table)
180
181 }

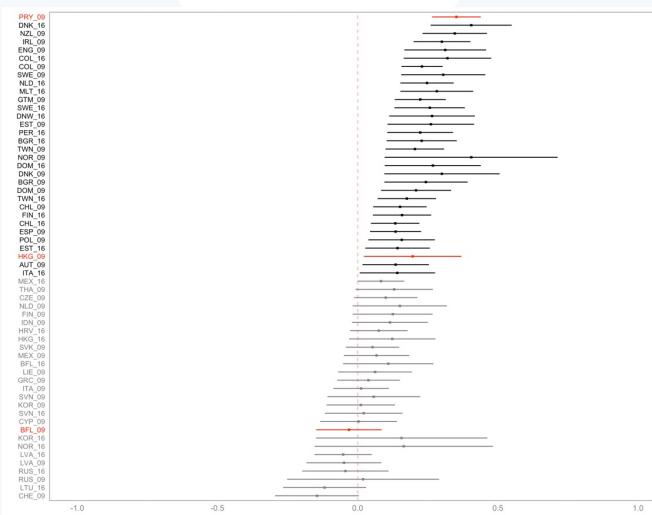
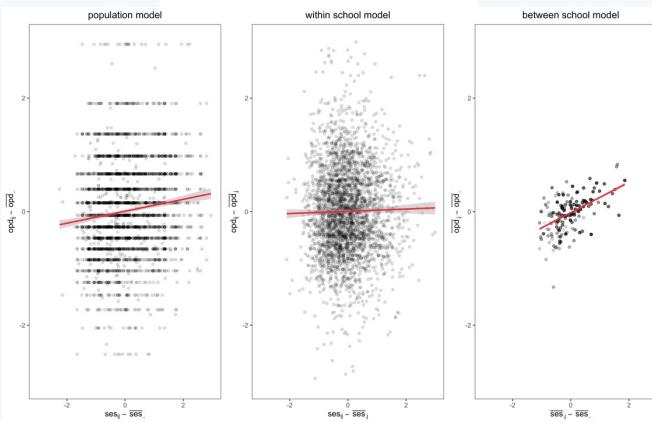
```

	> estimates_table	file	ctry	year	dep	cov	est	se	pval	star	ll	ul
1	1	fit_09_AUT.out	AUT	09	OPD	SES_B	0.135	0.060	0.025	*	0.017	0.254
2	2	fit_09_BFL.out	BFL	09	OPD	SES_B	-0.031	0.060	0.600		-0.148	0.085
3	3	fit_09_BGR.out	BGR	09	OPD	SES_B	0.243	0.076	0.001	**	0.095	0.392
4	4	fit_09_CHE.out	CHE	09	OPD	SES_B	-0.145	0.076	0.057		-0.295	0.004
5	5	fit_09_CHL.out	CHL	09	OPD	SES_B	0.151	0.049	0.002	**	0.055	0.246
6	6	fit_09_COL.out	COL	09	OPD	SES_B	0.229	0.038	0.000	***	0.156	0.303
7	7	fit_09_CYP.out	CYP	09	OPD	SES_B	0.003	0.070	0.968		-0.134	0.140
8	8	fit_09_CZE.out	CZE	09	OPD	SES_B	0.100	0.058	0.084		-0.013	0.213
9	9	fit_09_DNK.out	DNK	09	OPD	SES_B	0.300	0.105	0.004	**	0.095	0.506
10	10	fit_09_DOM.out	DOM	09	OPD	SES_B	0.208	0.064	0.001	**	0.083	0.333
11	11	fit_09_ENG.out	ENG	09	OPD	SES_B	0.312	0.074	0.000	***	0.166	0.458
12	12	fit_09_ESP.out	ESP	09	OPD	SES_B	0.135	0.046	0.004	**	0.044	0.226
13	13	fit_09_EST.out	EST	09	OPD	SES_B	0.261	0.079	0.001	**	0.106	0.415
14	14	fit_09_FIN.out	FIN	09	OPD	SES_B	0.125	0.072	0.086		-0.018	0.267
15	15	fit_09_GRC.out	GRC	09	OPD	SES_B	0.038	0.057	0.500		-0.073	0.150
16	16	fit_09_GTM.out	GTM	09	OPD	SES_B	0.223	0.046	0.000	***	0.132	0.314
17	17	fit_09_HKG.out	HKG	09	OPD	SES_B	0.196	0.089	0.027	*	0.022	0.370
18	18	fit_09_IDN.out	IDN	09	OPD	SES_B	0.115	0.069	0.097		-0.021	0.250
19	19	fit_09_IRL.out	IRL	09	OPD	SES_B	0.300	0.052	0.000	***	0.199	0.402
20	20	fit_09_ITA.out	ITA	09	OPD	SES_B	0.012	0.051	0.808		-0.087	0.111
21	21	fit_09_KOR.out	KOR	09	OPD	SES_B	0.011	0.062	0.858		-0.111	0.133
22	22	fit_09_LIE.out	LIE	09	OPD	SES_B	0.062	0.067	0.358		-0.070	0.193
23	23	fit_09_LVA.out	LVA	09	OPD	SES_B	-0.049	0.068	0.468		-0.183	0.084
24	24	fit_09_MEX.out	MEX	09	OPD	SES_B	0.067	0.059	0.257		-0.049	0.184
25	25	fit_09_NLD.out	NLD	09	OPD	SES_B	0.150	0.086	0.081		-0.018	0.318
26	26	fit_09_NOR.out	NOR	09	OPD	SES_B	0.405	0.157	0.010	*	0.096	0.713
27	27	fit_09_NZL.out	NZL	09	OPD	SES_B	0.346	0.059	0.000	***	0.231	0.461
28	28	fit_09_POL.out	POL	09	OPD	SES_B	0.157	0.060	0.009	**	0.038	0.275
29	29	fit_09_PRY.out	PRY	09	OPD	SES_B	0.352	0.044	0.000	***	0.265	0.439
30	30	fit_09_RUS.out	RUS	09	OPD	SES_B	0.019	0.138	0.889		-0.252	0.290
31	31	fit_09_SVK.out	SVK	09	OPD	SES_B	0.053	0.048	0.271		-0.042	0.148
32	32	fit_09 SVN.out	SVN	09	OPD	SES_B	0.057	0.084	0.495		-0.108	0.223
33	33	fit_09_SWE.out	SWE	09	OPD	SES_B	0.305	0.076	0.000	***	0.155	0.455
34	34	fit_09_THA.out	THA	09	OPD	SES_B	0.130	0.070	0.065		-0.008	0.268
35	35	fit_09_TWN.out	TWN	09	OPD	SES_B	0.204	0.053	0.000	***	0.099	0.308
36	36	fit_16_BFL.out	BFL	16	OPD	SES_B	0.109	0.082	0.183		-0.052	0.270
37	37	fit_16_BGR.out	BGR	16	OPD	SES_B	0.228	0.064	0.000	***	0.103	0.353
38	38	fit_16_CHL.out	CHL	16	OPD	SES_B	0.134	0.044	0.002	**	0.047	0.220
39	39	fit_16_COL.out	COL	16	OPD	SES_B	0.320	0.080	0.000	***	0.164	0.476
40	40	fit_16_DNK.out	DNK	16	OPD	SES_B	0.405	0.074	0.000	***	0.260	0.549
41	41	fit_16_DNW.out	DNW	16	OPD	SES_B	0.265	0.078	0.001	**	0.112	0.418
42	42	fit_16_DOM.out	DOM	16	OPD	SES_B	0.268	0.088	0.002	**	0.096	0.439
43	43	fit_16_EST.out	EST	16	OPD	SES_B	0.142	0.059	0.016	*	0.027	0.257
44	44	fit_16_FIN.out	FIN	16	OPD	SES_B	0.158	0.053	0.003	**	0.054	0.262
45	45	fit_16_HKG.out	HKG	16	OPD	SES_B	0.123	0.079	0.117		-0.031	0.277
46	46	fit_16_HRV.out	HRV	16	OPD	SES_B	0.075	0.052	0.149		-0.027	0.178
47	47	fit_16_ITA.out	ITA	16	OPD	SES_B	0.141	0.069	0.040	*	0.007	0.276
48	48	fit_16_KOR.out	KOR	16	OPD	SES_B	0.156	0.156	0.316		-0.149	0.462
49	49	fit_16_LTU.out	LTU	16	OPD	SES_B	-0.118	0.076	0.118		-0.266	0.030
50	50	fit_16_LVA.out	LVA	16	OPD	SES_B	-0.052	0.052	0.313		-0.154	0.050
51	51	fit_16_MEX.out	MEX	16	OPD	SES_B	0.083	0.042	0.049	*	0.000	0.166
52	52	fit_16_MLT.out	MLT	16	OPD	SES_B	0.282	0.066	0.000	***	0.152	0.412
53	53	fit_16_NLD.out	NLD	16	OPD	SES_B	0.247	0.048	0.000	***	0.152	0.342
54	54	fit_16_NOR.out	NOR	16	OPD	SES_B	0.164	0.162	0.312		-0.154	0.482
55	55	fit_16_PER.out	PER	16	OPD	SES_B	0.223	0.060	0.000	***	0.105	0.340
56	56	fit_16_RUS.out	RUS	16	OPD	SES_B	-0.044	0.079	0.574		-0.198	0.110
57	57	fit_16_SVN.out	SVN	16	OPD	SES_B	0.021	0.071	0.762		-0.117	0.160
58	58	fit_16_SWE.out	SWE	16	OPD	SES_B	0.257	0.064	0.000	***	0.131	0.382
59	59	fit_16_TWN.out	TWN	16	OPD	SES_B	0.175	0.053	0.001	**	0.071	0.279

We retrieve all estimates from the 59 fitted models and generate tables and plots.

05_descriptives_plots.rmd

```
304 #
305 # grid plot
306 #
307 #
308 cowplot::plot_grid(p1, p2, p3, ncol=3)
309 #
310 #
311 # save plot
312 #
313 #
314 ggsave(paste0(plot_folder,file_text,'.png'),
315   plot = last_plot(),
316   width = 16,
317   height = 10,
318   units = 'cm',
319   dpi = 400,
320   scale = 2)
321 #
322 #
323 # display plot
324 #
325 #
326 return(cowplot::plot_grid(p1, p2, p3, ncol=3))
327 }
328 #
329 #
330 #
331 # list of countries
332 #
333 #
334 dplyr::count(opd_09, COUNTRY) %>%
335 knitr::kable()
336 #
337 dplyr::count(opd_16, COUNTRY) %>%
338 knitr::kable()
339 #
340 #
341 #
342 #
343 #
344 # Selected Plot
345 #
346 ```{r echo=FALSE}
347 #
348 #
349 # make grid plot
350 #
351 #
352 #
353 plot_effects(data = opd_09, country = 'PRY', 'pry_2009')
354 plot_effects(data = opd_09, country = 'HKG', 'hkg_2009')
355 plot_effects(data = opd_09, country = 'BFL', 'bfl_2009')
```



Using the table of estimates, and the study data different plots can be generated to present the main results.

Towards a tidy framework for large scale assessment

- Data analysis as code development (Parker, 2017)
- Statistical code could be
 - Reproducible
 - Auditible
 - Precise
 - Collaborative



Muchas gracias!

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Treviño, E., PhD

https://github.com/dacarras/cies_2021_opd