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

65th Annual Conference of the Comparative and International Education Society (CIES)

vCIES 2021, April 29th, 2021

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https://github.com/dacarras/cies_2021_opd

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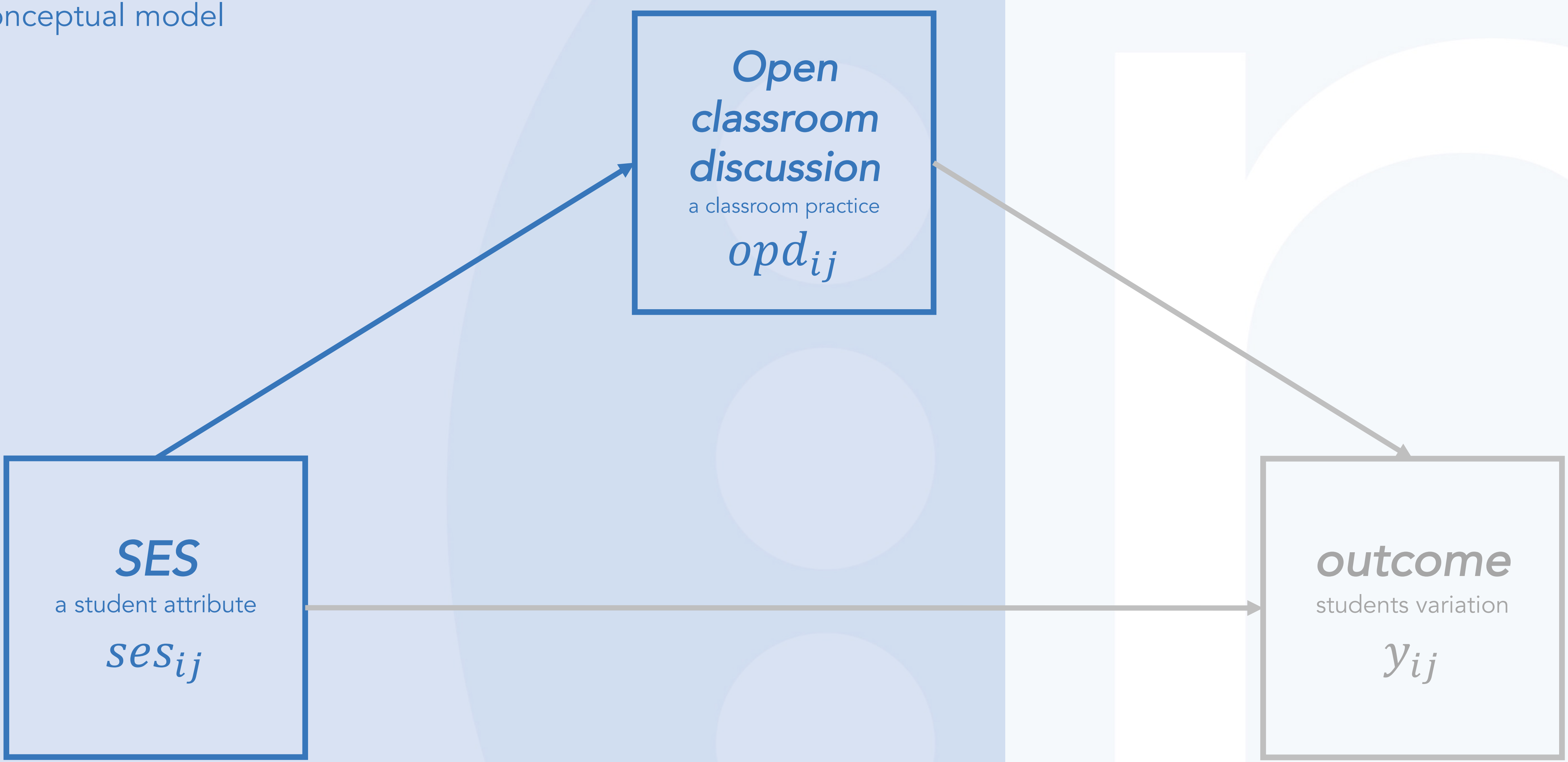
Unequal access to

Open classroom discussion

Opportunity learning gaps

Conceptual model



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)

Disadvantage 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)

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 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)

$$opd_{ij} = \alpha + \boldsymbol{\delta}_t ses_{ij} + \epsilon_{ij}$$

Within school model

How students perceive the attribute across schools?

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

$$opd_{ij} = \alpha + \boldsymbol{\delta}_w (ses_{ij} - \overline{ses}_{..}) + \ldots + \theta_{.j} + \epsilon_{ij}$$

Between school model

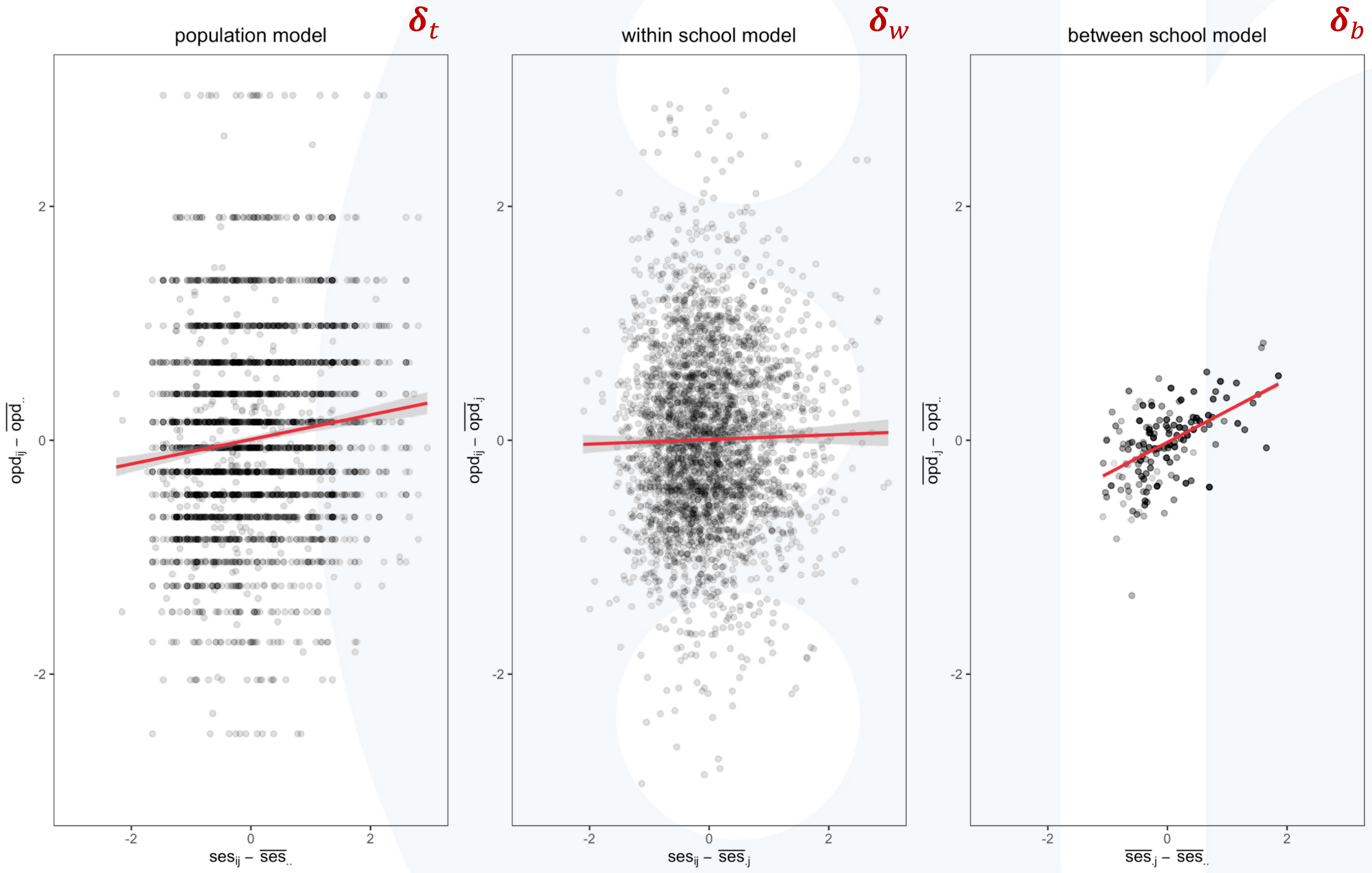
What is the most likely school they are attending to?

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

$$opd_{ij} = \alpha + \boldsymbol{\delta}_w (ses_{ij} - \overline{ses}_{.j}) + \boldsymbol{\delta}_b (\overline{ses}_{.j} - \overline{ses}_{..}) + \theta_{.j} + \epsilon_{ij}$$

Different coefficients

opd = open classroom discussion



ses = socioecionomic status

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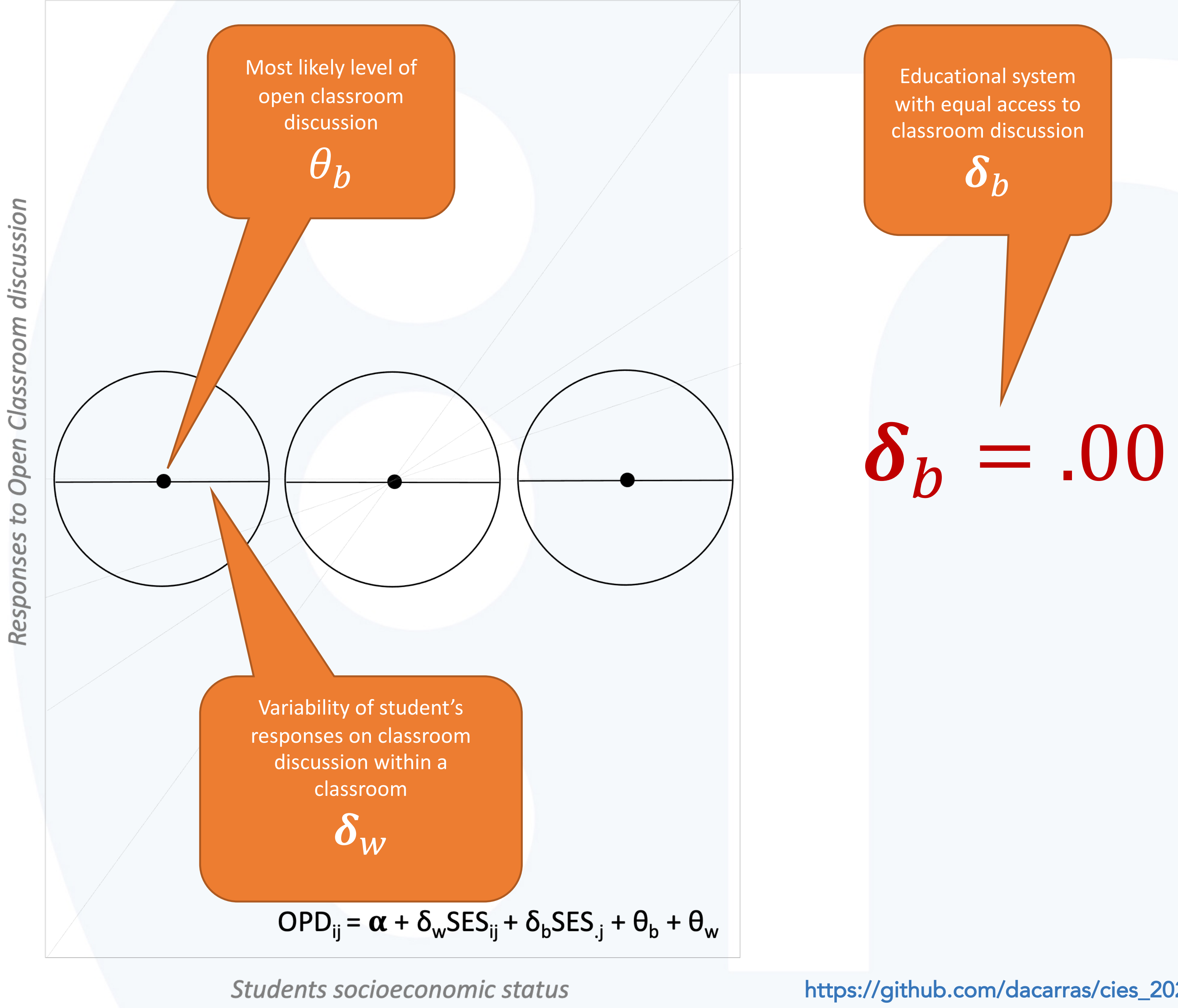
https://github.com/dacarras/cies_2021_opd

Opportunities learning gaps

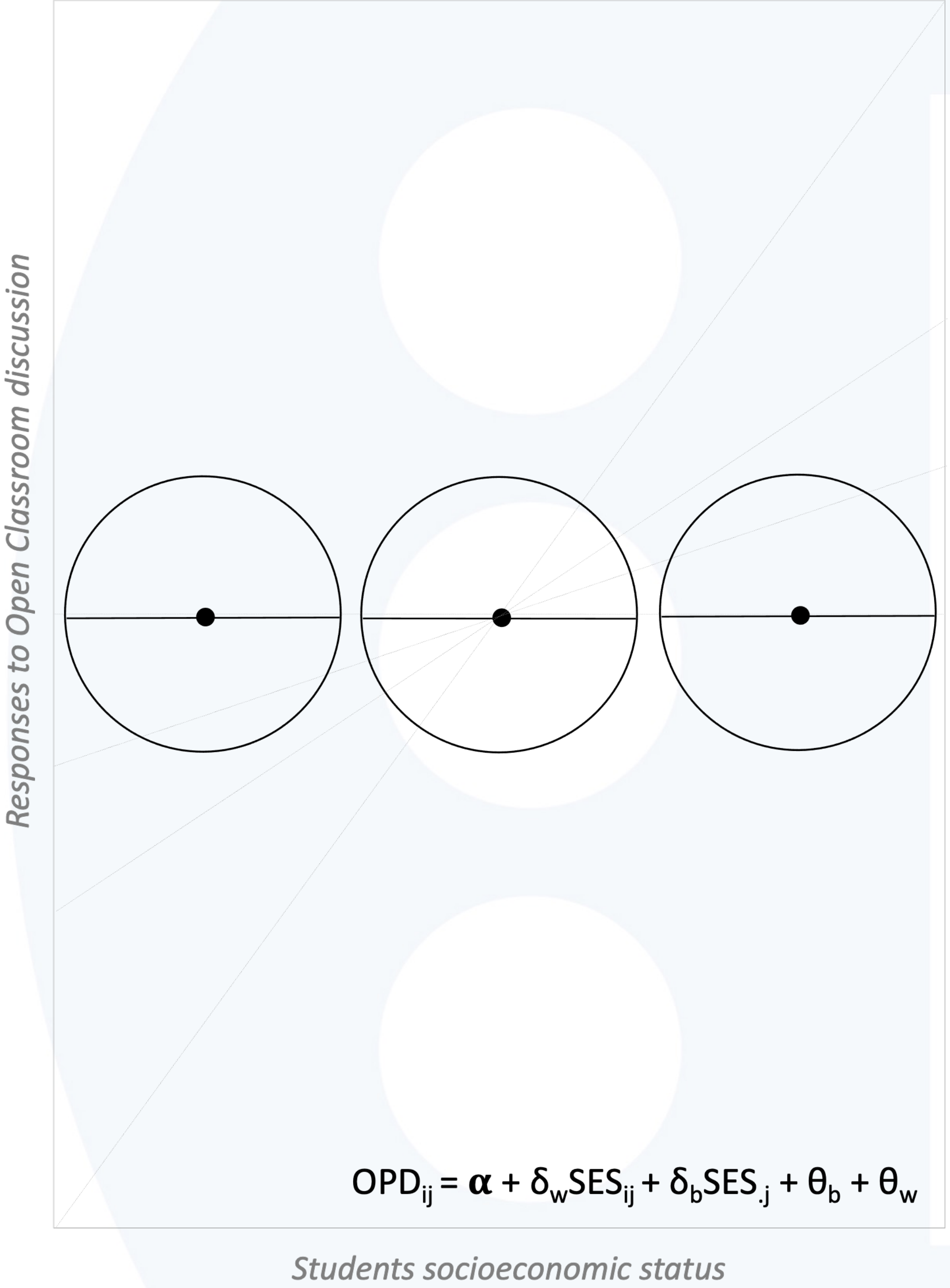
Coefficients representation

Geometric projection

Coefficient Representation



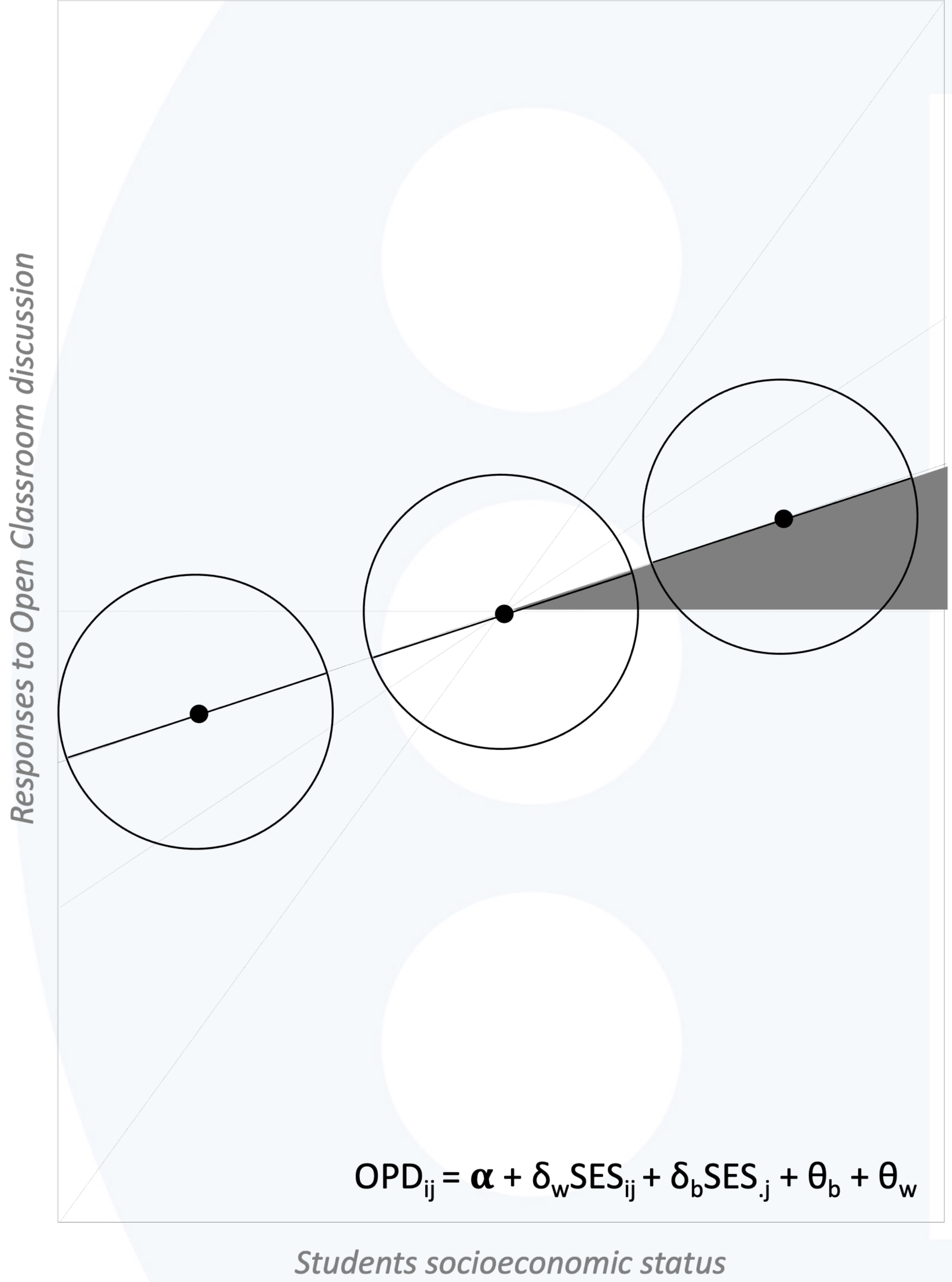
Coefficient Representation



$$\delta_b = .00$$

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

Coefficient Representation

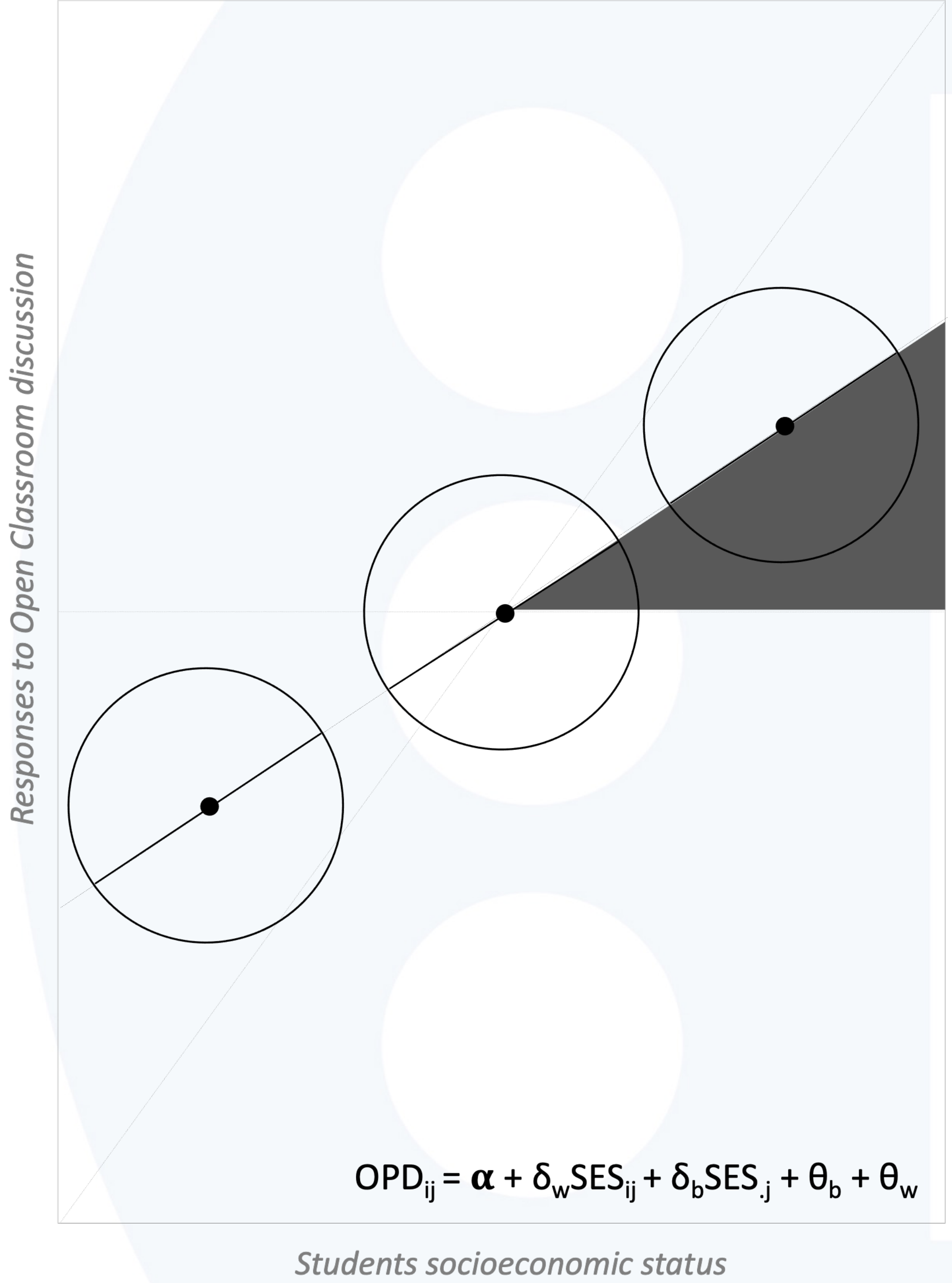


$$\boldsymbol{\delta}_b = .25$$

There is some noticeble gap

https://github.com/dacarras/cies_2021_opd

Coefficient Representation

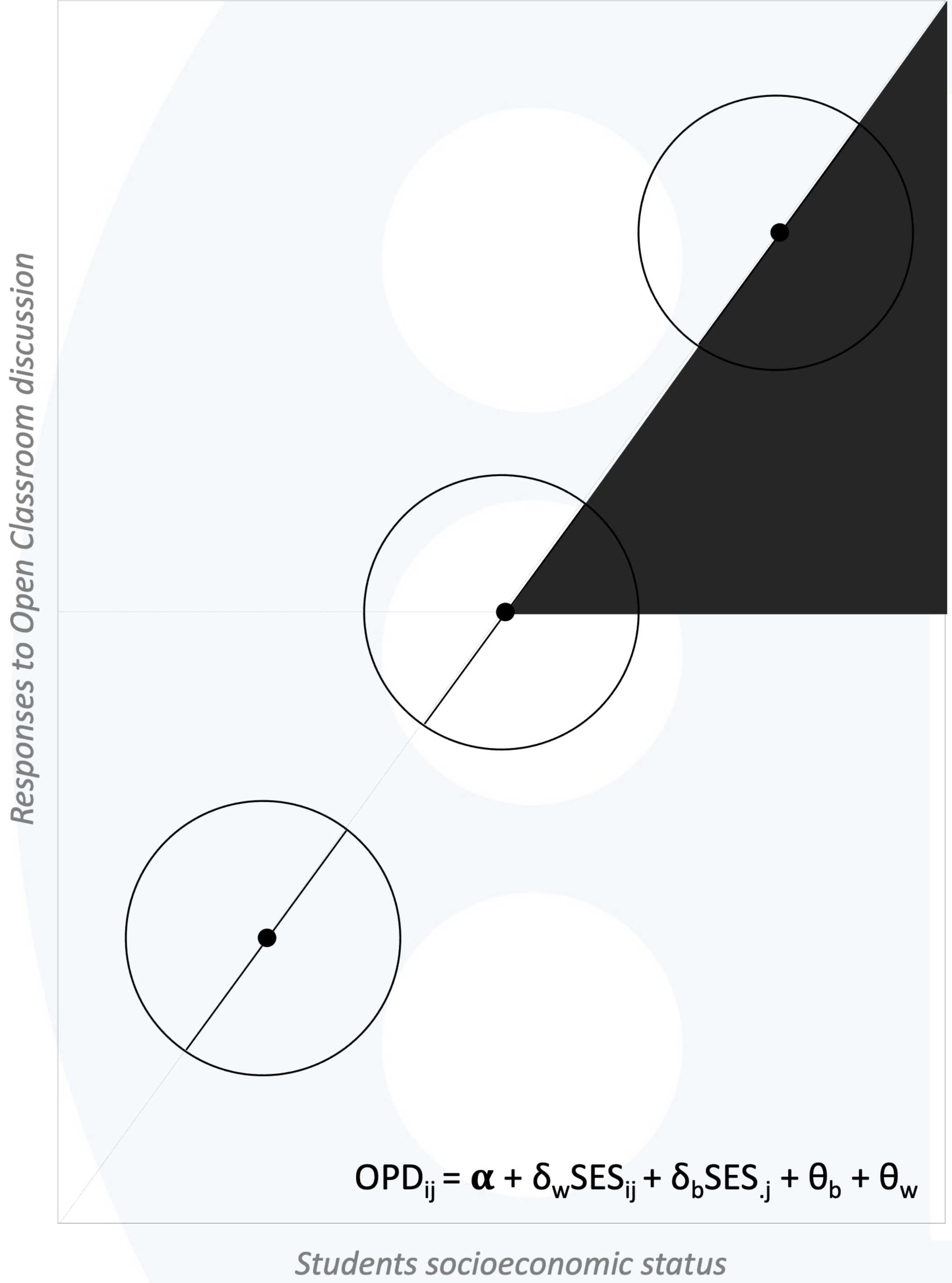


$\boldsymbol{\delta}_b = .50$

There is a large gap on access

https://github.com/dacarras/cies_2021_opd

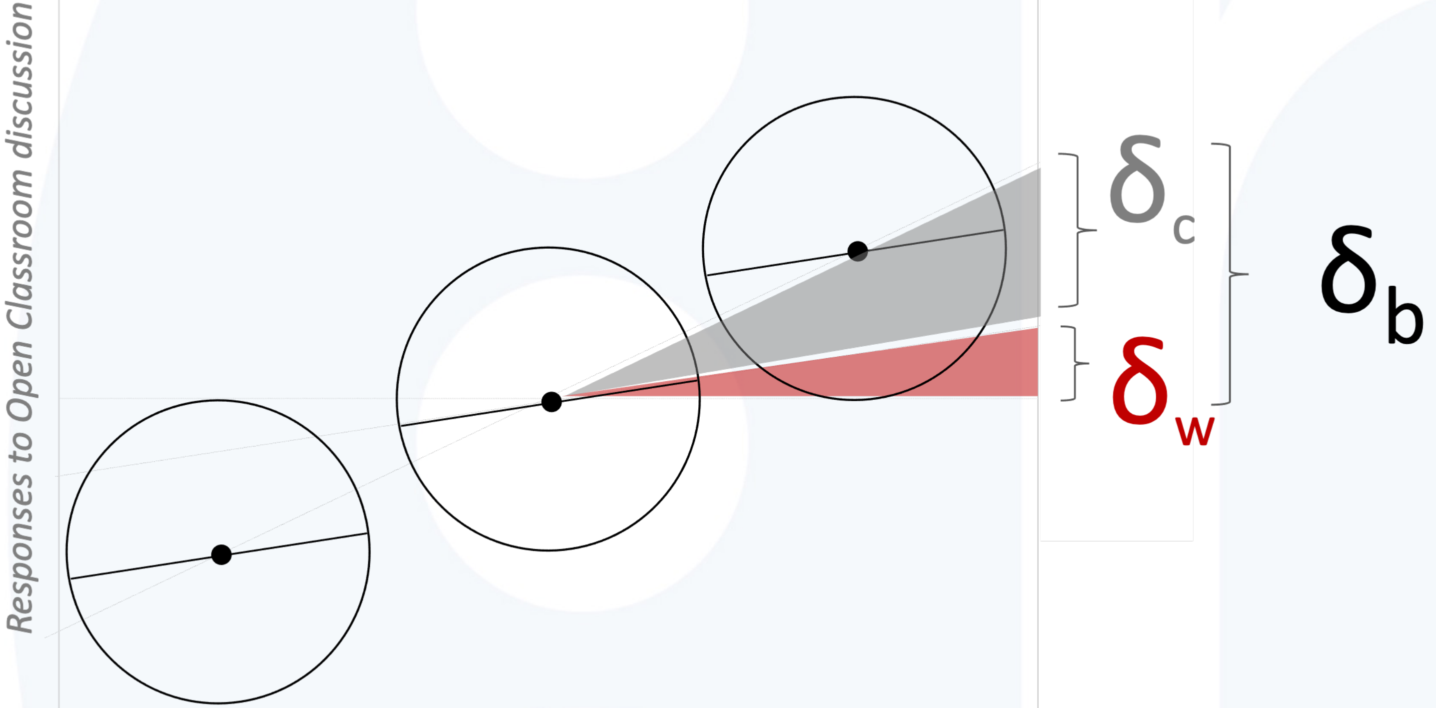
Coefficient Representation



$$\delta_b = 1.00$$

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

Coefficient Representation



$$OPD_{ij} = \boldsymbol{\alpha} + \delta_w SES_{ij} + \delta_b SES_{.j} + \theta_b + \theta_w$$

Students socioeconomic status

Generic scenario:
there could be some gap

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

$$opd_{ij} = \alpha + \boldsymbol{\delta}_w(ses_{ij} - \overline{ses}_{.j}) + \boldsymbol{\delta}_b(\overline{ses}_{.j} - \overline{ses}_{..}) + \theta_{.j} + \epsilon_{ij}$$

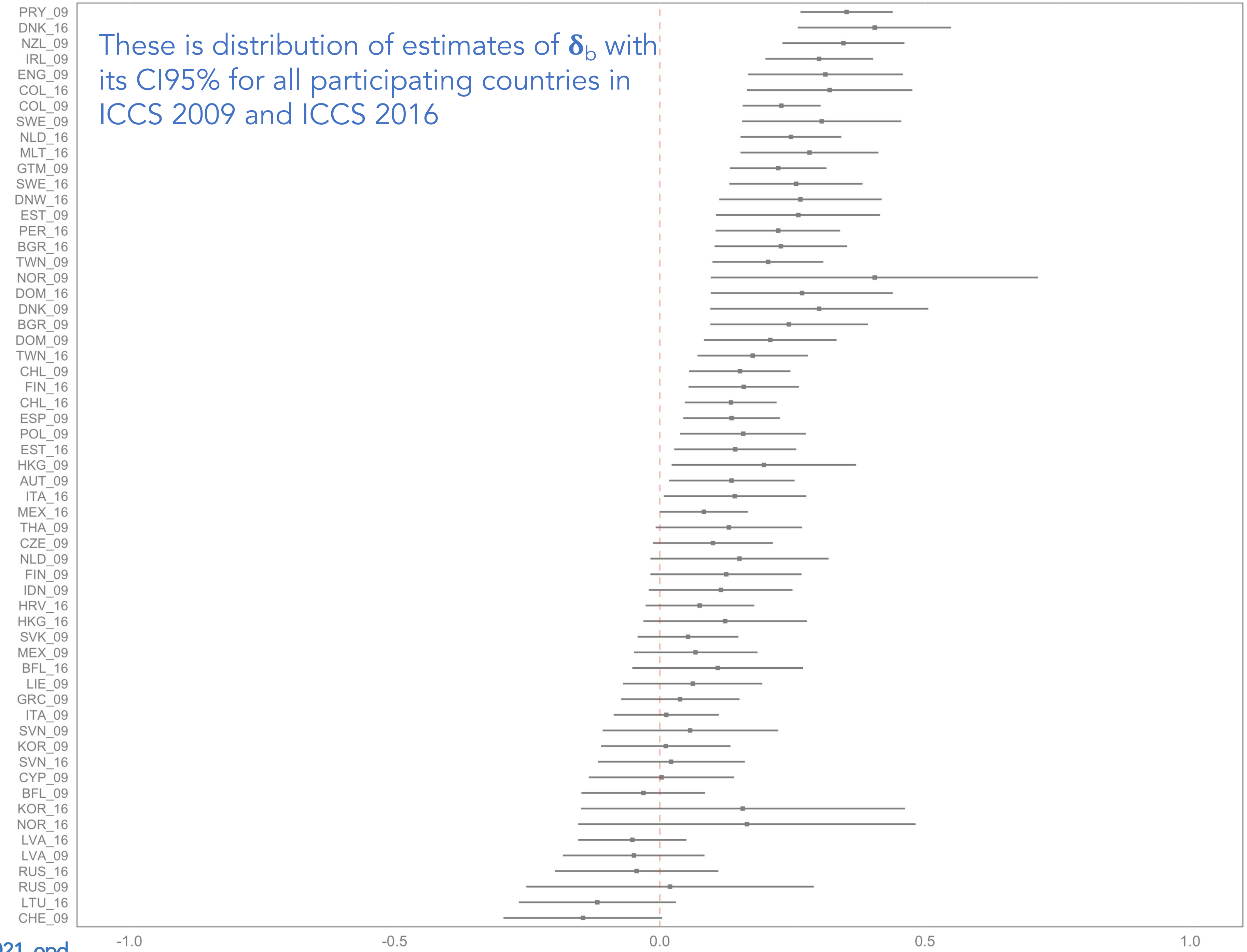
  - opd_{ij} scores are standardized using the international scale score. These are centered at zero, and have a standard deviation of 1, across all countries.
  - Pseudo Maximum Likelihood estimation with effective sample size weight scalling (Stapleton, 2013)
  - Models are fitted using Mplus via MplusAutomation package (Hallquist & Wiley, 2018)

Oportunities learning gaps

What results we got

Results

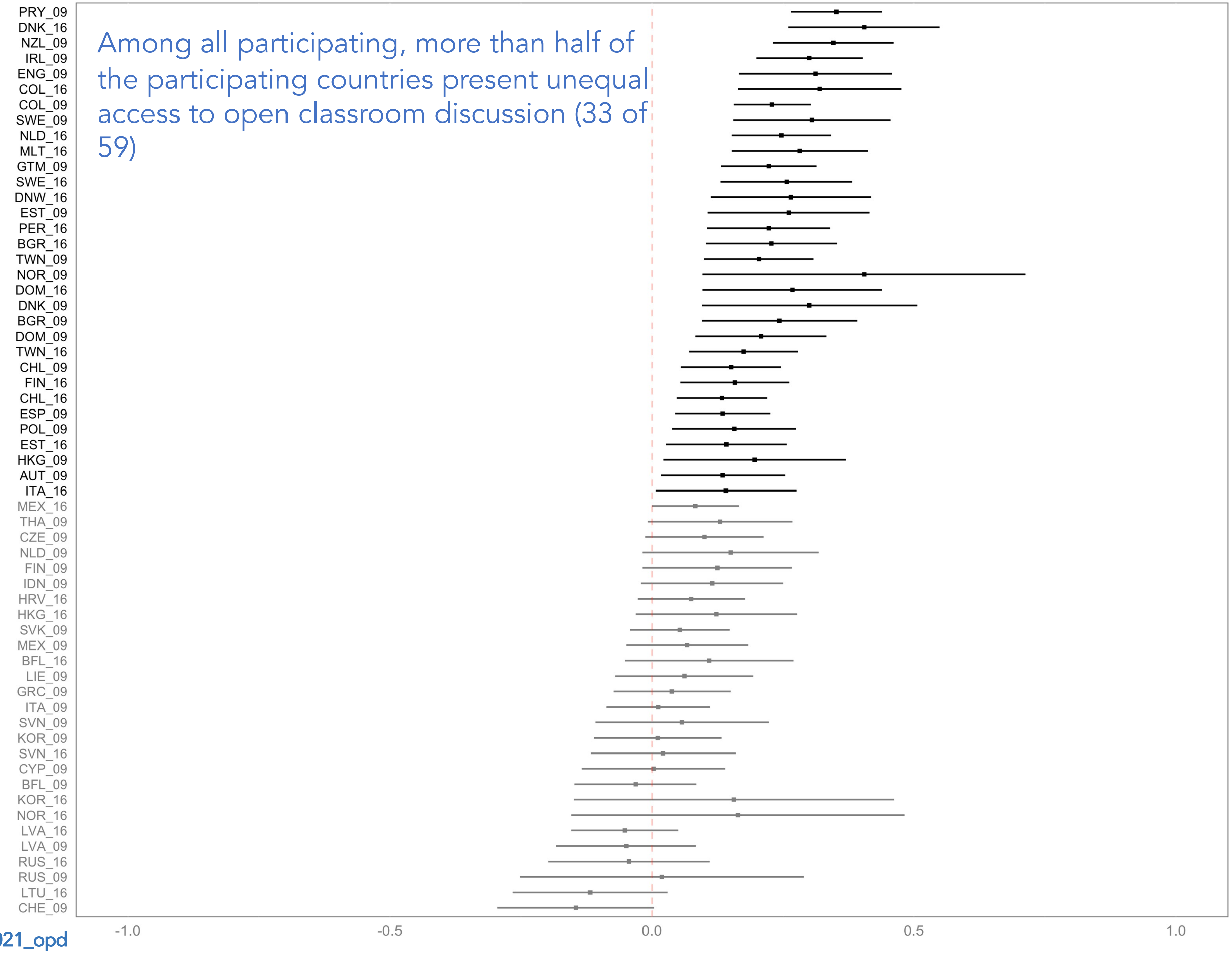
Results



These is distribution of estimates of $\boldsymbol{\delta}_b$ with its CI95% for all participating countries in ICCS 2009 and ICCS 2016
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
-1.0
-0.5
0.0
0.5
1.0

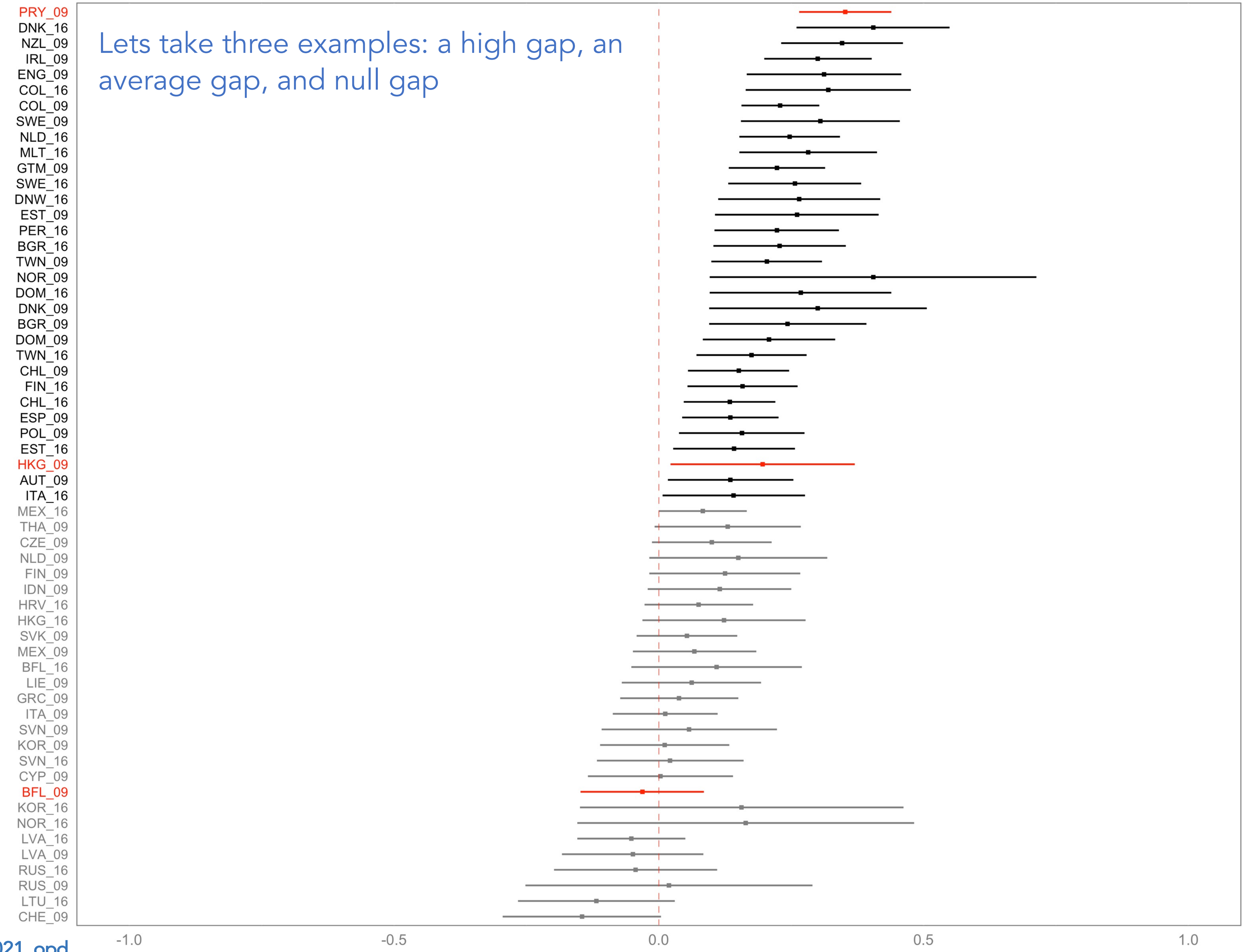
Results

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



Results

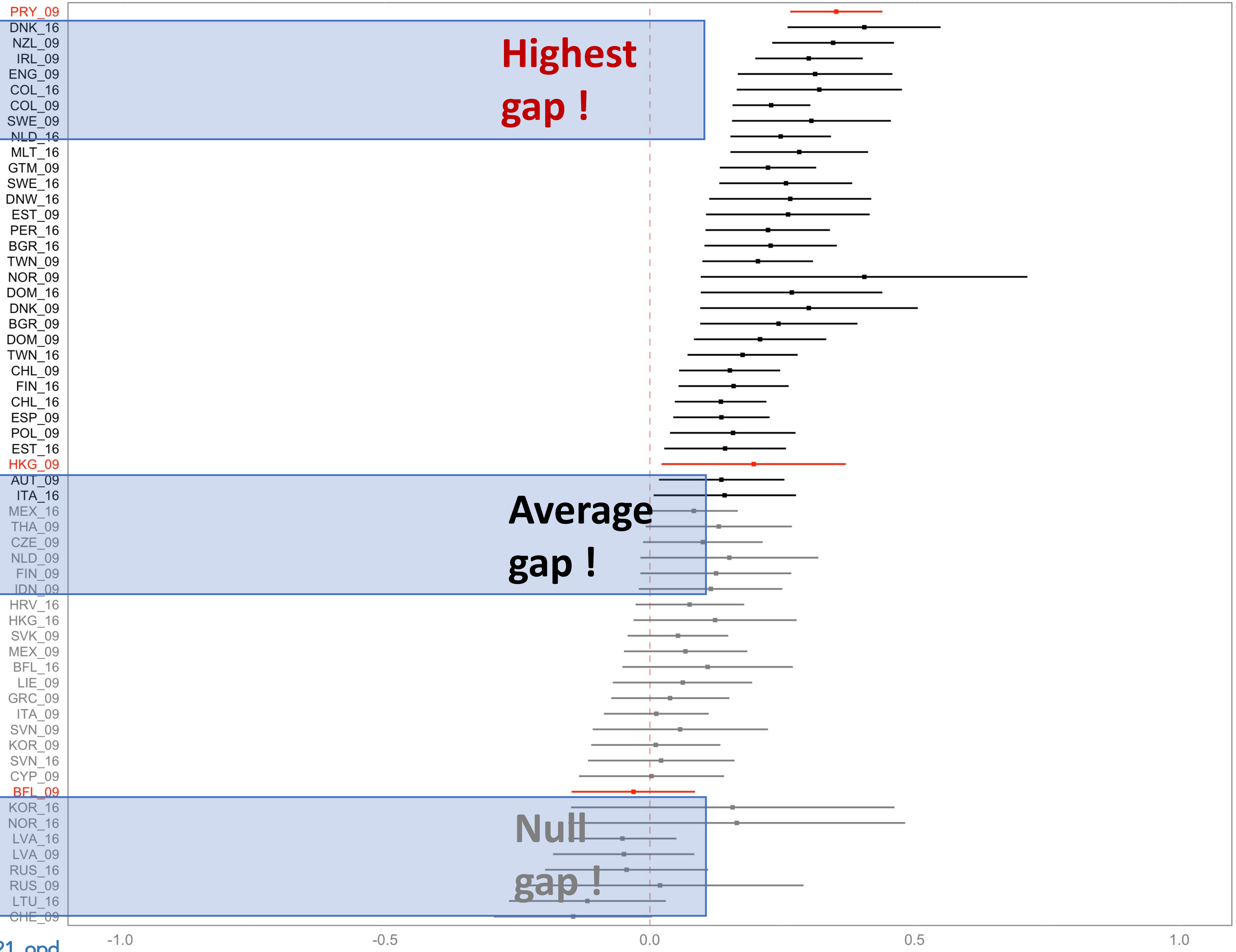
Lets take three examples: a high gap, an average gap, and null gap



Paraguay ICCS 2009

δ_b=.35 CI95%[.26, .44]

Highest gap !



Hong Kong ICCS 2009

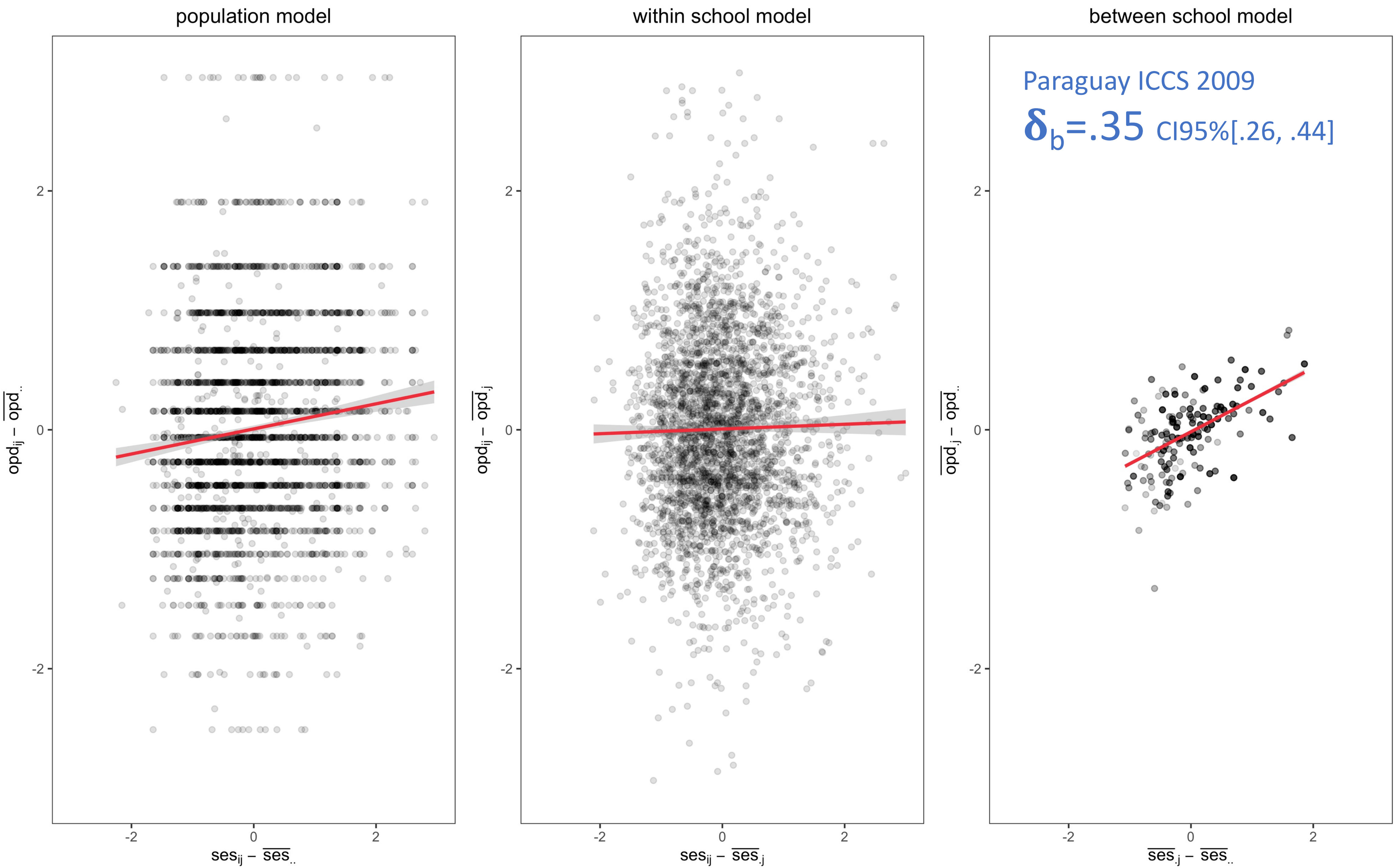
δ_b=.20 CI95%[.02, .37]

Average gap !

Belgium (Flemish) ICCS 2009

δ_b=-.03 CI95%[-0.15, .09]

Null gap !



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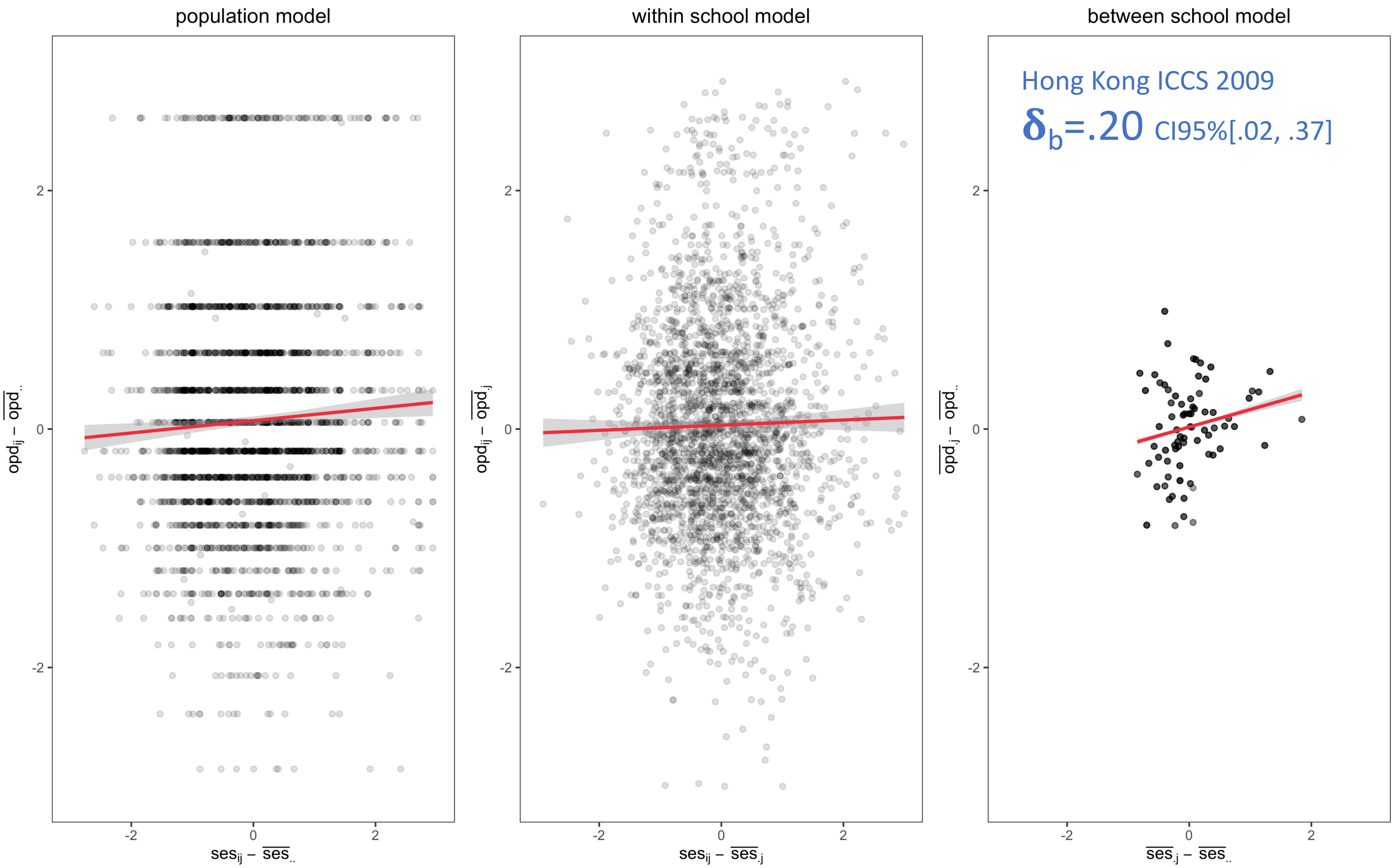

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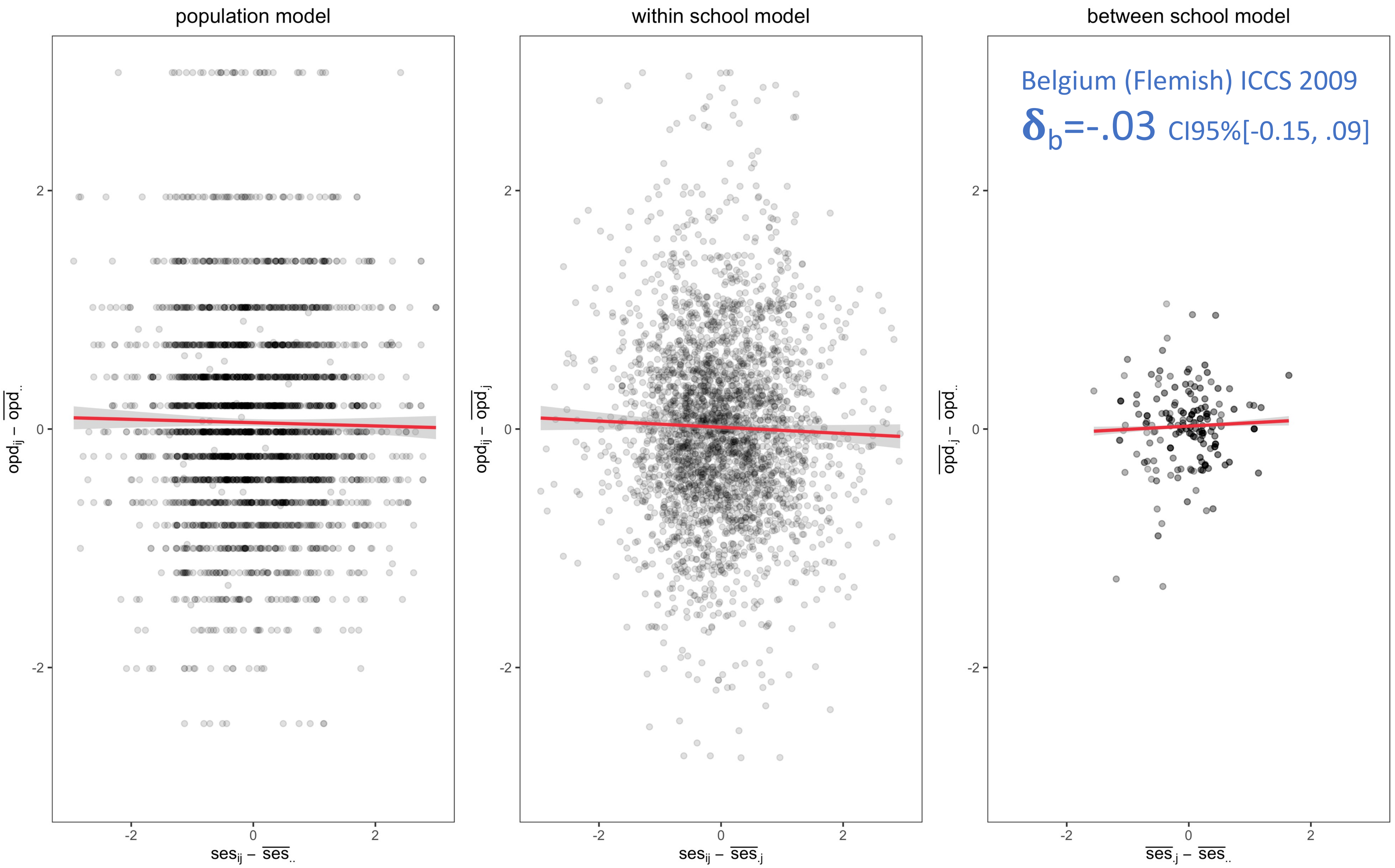

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Oportunities learning gaps

What was our workflow

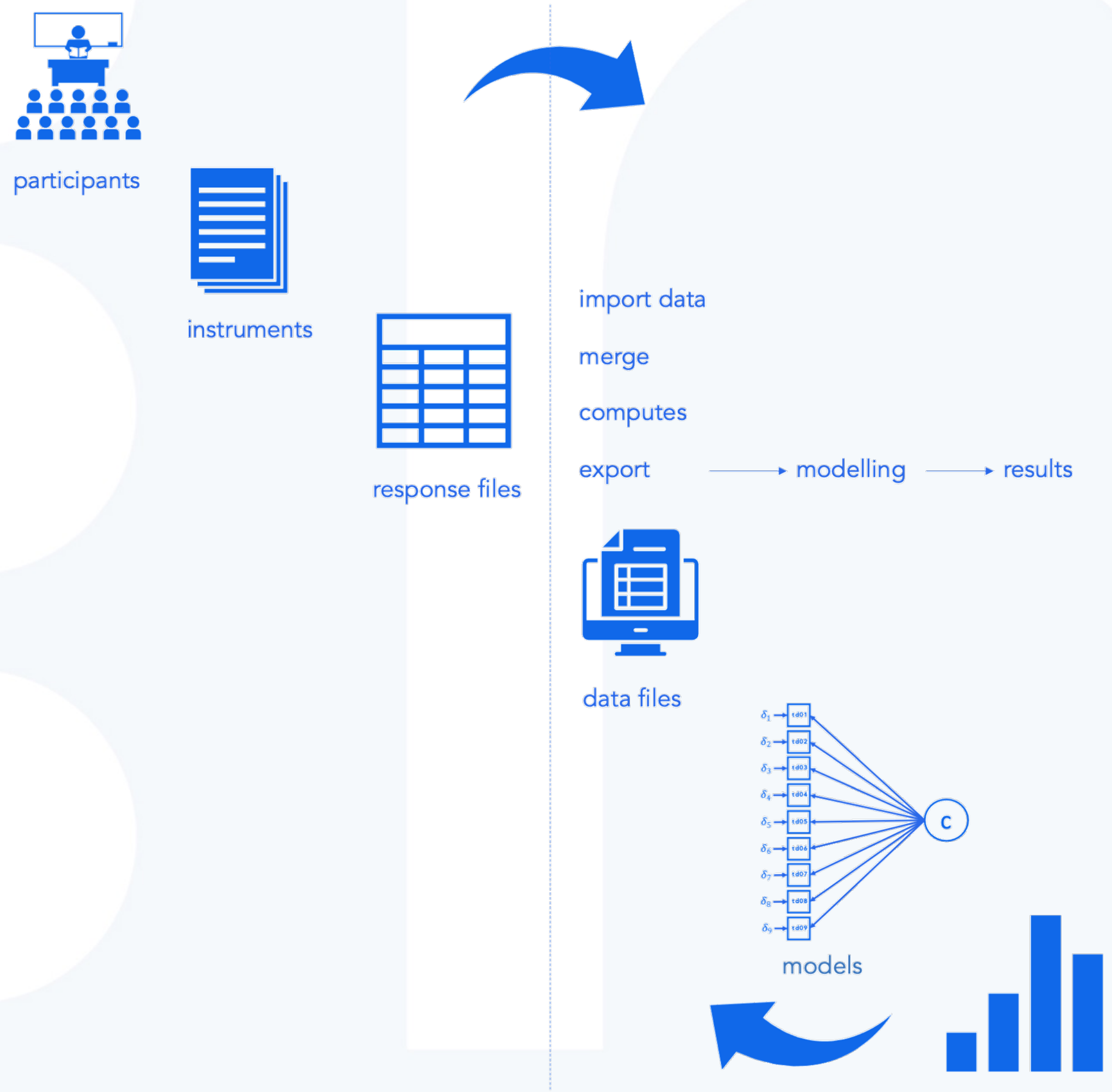
How to replicate the current results

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 weights
- Fit Models
  - Specify model
  - Fit as many models are needed
- Process estimates
  - Parse output into readable objects
- Summarize results
  - Tables
  - Figure



Data Analysis workflow

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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

```
# ------------------------------------------------------------------------------
# import all data
# ------------------------------------------------------------------------------

# -----------------------------------------------
# get list of files
# -----------------------------------------------

iccs_2009_files <- paste0(data_folder, list.files(path = data_folder, pattern = "C2.*"))
iccs_2016_files <- paste0(data_folder, list.files(path = data_folder, pattern = "C3.*"))

# -----------------------------------------------
# import all and merge
# -----------------------------------------------

library(dplyr)
iccs_2009 <- iccs_2009_files %>%
             purrr::map_df(haven::read_sav)

library(dplyr)
iccs_2016 <- iccs_2016_files %>%
             purrr::map_df(haven::read_sav)

```

02_prepare_data.rmd

```r

data_09 <- readRDS(paste0(data_folder, 'iccs_2009_stu_int.rds'))

# ----------------------------------------------
# generic survey design variables
# ----------------------------------------------

library(dplyr)
data_model_09 <- data_09 %>%
                 # remove labels
                 r4sda::remove_labels() %>%
                 # clustering
                 mutate(id_i = seq(1:nrow(.))) %>%
                 mutate(id_j = as.numeric(as.factor(paste0(COUNTRY, JKZONES, IDSCHOOL)))) %>%
                 mutate(id_s = as.numeric(as.factor(paste0(COUNTRY, JKZONES)))) %>%
                 mutate(id_r = as.numeric(as.factor(paste0(COUNTRY, JKZONES, JKREPS)))) %>%
                 mutate(id_k = as.numeric(as.factor(paste0(COUNTRY)))) %>%
                 # survey weights
                 mutate(wt = TOTWGTS) %>%
                 # students weights
                 mutate(wi = WGTFAC2S*WGTADJ2S*WGTADJ3S) %>%
                 # school weights
                 mutate(wj = WGTFAC1*WGTADJ1S) %>%
                 # create senate weights
                 r4sda::senate_weights(., wt = 'wt', id_k = 'id_k', scale = 1000) %>%
                 # create scaled weights
                 r4sda::lsa_weights(.,
                   id_i = 'id_i',
                   id_j = 'id_j',
                   id_k = 'id_k',
                   wt = 'wt',
                   wi = 'wi',
                   wj = 'wj') %>%
                 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

```r
library(MplusAutomation)
oportunity_gap_model <- mplusObject(
MODEL = '

%WITHIN%
opd on ses_w (w);


%BETWEEN%
opd on ses_b (b);

',
ANALYSIS = '
TYPE = TWOLEVEL COMPLEX;
ESTIMATOR = MLR;
',

VARIABLE = '
! variables with restricted variance
WITHIN  = ses_w;
BETWEEN = ses_b;

!complex sample design
STRATIFICATION = id_s;
CLUSTER = id_j;

!multilevel specification
WEIGHT  = wi;
BWEIGHT = wj;
WTSCALE = ECLUSTER;
BWTSCALE = SAMPLE;

USEVARIABLES =
opd
ses_w
ses_b
;
',
MODELCONSTRAINT =
'
new (
ce_w
ce_b
ce_c
);

!contextual effect of ses
ce_w = w;
ce_b = b;
ce_c = b - w;
',
OUTPUT ='
STAND
TECH1
TECH3
SAMPSTAT
CINTERVAL
;
',
rdata = opd_09_CHL)
```

```r
# ----------------------------------------
# fit models
# ----------------------------------------

fit_09_AUT <- mplusModeler(gap_09_AUT, modelout = 'fit_09_AUT.inp', run = 1L, hashfilename = FALSE)
fit_09_BGR <- mplusModeler(gap_09_BGR, modelout = 'fit_09_BGR.inp', run = 1L, hashfilename = FALSE)
fit_09_CHL <- mplusModeler(gap_09_CHL, modelout = 'fit_09_CHL.inp', run = 1L, hashfilename = FALSE)
fit_09_TWN <- mplusModeler(gap_09_TWN, modelout = 'fit_09_TWN.inp', run = 1L, hashfilename = FALSE)
fit_09_COL <- mplusModeler(gap_09_COL, modelout = 'fit_09_COL.inp', run = 1L, hashfilename = FALSE)
fit_09_CYP <- mplusModeler(gap_09_CYP, modelout = 'fit_09_CYP.inp', run = 1L, hashfilename = FALSE)
fit_09_CZE <- mplusModeler(gap_09_CZE, modelout = 'fit_09_CZE.inp', run = 1L, hashfilename = FALSE)
fit_09_DNK <- mplusModeler(gap_09_DNK, modelout = 'fit_09_DNK.inp', run = 1L, hashfilename = FALSE)
fit_09_DOM <- mplusModeler(gap_09_DOM, modelout = 'fit_09_DOM.inp', run = 1L, hashfilename = FALSE)
fit_09_EST <- mplusModeler(gap_09_EST, modelout = 'fit_09_EST.inp', run = 1L, hashfilename = FALSE)
fit_09_FIN <- mplusModeler(gap_09_FIN, modelout = 'fit_09_FIN.inp', run = 1L, hashfilename = FALSE)
fit_09_GRC <- mplusModeler(gap_09_GRC, modelout = 'fit_09_GRC.inp', run = 1L, hashfilename = FALSE)
fit_09_GTM <- mplusModeler(gap_09_GTM, modelout = 'fit_09_GTM.inp', run = 1L, hashfilename = FALSE)
fit_09_HKG <- mplusModeler(gap_09_HKG, modelout = 'fit_09_HKG.inp', run = 1L, hashfilename = FALSE)
fit_09_IDN <- mplusModeler(gap_09_IDN, modelout = 'fit_09_IDN.inp', run = 1L, hashfilename = FALSE)
fit_09_IRL <- mplusModeler(gap_09_IRL, modelout = 'fit_09_IRL.inp', run = 1L, hashfilename = FALSE)
fit_09_ITA <- mplusModeler(gap_09_ITA, modelout = 'fit_09_ITA.inp', run = 1L, hashfilename = FALSE)
fit_09_KOR <- mplusModeler(gap_09_KOR, modelout = 'fit_09_KOR.inp', run = 1L, hashfilename = FALSE)
fit_09_LVA <- mplusModeler(gap_09_LVA, modelout = 'fit_09_LVA.inp', run = 1L, hashfilename = FALSE)
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

````
# read all
model_estimates <- MplusAutomation::readModels(target = paste0(syntax_folder))

# there should be 59 estimates models
length(model_estimates)

```

## Standardized

```{r , echo=TRUE}

#------------------------------------------------------------------------------
# extract estimates
#------------------------------------------------------------------------------

# ----------------------------------------
# pseudo function to get estimates
# ----------------------------------------

get_est <- function(model_estimates, object) {

require(dplyr)

numeric <- object

estimates <- model_estimates[[numeric]]$parameters$unstandardized %>%
            dplyr::filter(param == 'SES_B') %>%
            mutate(star = case_when(
            pval < .001 ~ '***',
            pval < .01  ~ '** ',
            pval < .05  ~ '*  ',
            pval >= .05 ~ '')) %>%
            mutate(dep = stringr::str_remove(paramHeader, '.ON')) %>%
            mutate(cov = param) %>%
            mutate(file = model_estimates[[numeric]]$summaries$Filename) %>%
            dplyr::select(dep, cov, est, se, pval, star, file)

ci_level <- model_estimates[[numeric]]$parameters$ci.unstandardized %>%
            dplyr::filter(param == 'SES_B') %>%
            mutate(level = BetweenWithin) %>%
            mutate(ll = low2.5) %>%
            mutate(ul = up2.5) %>%
            mutate(dep = stringr::str_remove(paramHeader, '.ON')) %>%
            mutate(cov = param) %>%
            dplyr::select(cov, ll, ul)

table <- dplyr::left_join(estimates, ci_level, by = 'cov') %>%
            mutate(ctry = stringr::str_remove(file, '.out')) %>%
            mutate(ctry = stringr::str_remove(ctry, 'fit_09_')) %>%
            mutate(ctry = stringr::str_remove(ctry, 'fit_16_')) %>%
            mutate(year = dplyr::if_else(stringr::str_detect(file, '16'),'16','09')) %>%
            dplyr::select(file, ctry, year, dep, cov, est, se, pval, star, ll, ul)

return(table)

}
````

```
> estimates_table
             file ctry year dep   cov    est    se  pval star     ll    ul
1  fit_09_AUT.out  AUT   09 OPD SES_B  0.135 0.060 0.025 *     0.017 0.254
2  fit_09_BFL.out  BFL   09 OPD SES_B -0.031 0.060 0.600      -0.148 0.085
3  fit_09_BGR.out  BGR   09 OPD SES_B  0.243 0.076 0.001 **    0.095 0.392
4  fit_09_CHE.out  CHE   09 OPD SES_B -0.145 0.076 0.057      -0.295 0.004
5  fit_09_CHL.out  CHL   09 OPD SES_B  0.151 0.049 0.002 **    0.055 0.246
6  fit_09_COL.out  COL   09 OPD SES_B  0.229 0.038 0.000 ***   0.156 0.303
7  fit_09_CYP.out  CYP   09 OPD SES_B  0.003 0.070 0.968      -0.134 0.140
8  fit_09_CZE.out  CZE   09 OPD SES_B  0.100 0.058 0.084      -0.013 0.213
9  fit_09_DNK.out  DNK   09 OPD SES_B  0.300 0.105 0.004 **    0.095 0.506
10 fit_09_DOM.out  DOM   09 OPD SES_B  0.208 0.064 0.001 **    0.083 0.333
11 fit_09_ENG.out  ENG   09 OPD SES_B  0.312 0.074 0.000 ***   0.166 0.458
12 fit_09_ESP.out  ESP   09 OPD SES_B  0.135 0.046 0.004 **    0.044 0.226
13 fit_09_EST.out  EST   09 OPD SES_B  0.261 0.079 0.001 **    0.106 0.415
14 fit_09_FIN.out  FIN   09 OPD SES_B  0.125 0.072 0.086      -0.018 0.267
15 fit_09_GRC.out  GRC   09 OPD SES_B  0.038 0.057 0.500      -0.073 0.150
16 fit_09_GTM.out  GTM   09 OPD SES_B  0.223 0.046 0.000 ***   0.132 0.314
17 fit_09_HKG.out  HKG   09 OPD SES_B  0.196 0.089 0.027 *     0.022 0.370
18 fit_09_IDN.out  IDN   09 OPD SES_B  0.115 0.069 0.097      -0.021 0.250
19 fit_09_IRL.out  IRL   09 OPD SES_B  0.300 0.052 0.000 ***   0.199 0.402
20 fit_09_ITA.out  ITA   09 OPD SES_B  0.012 0.051 0.808      -0.087 0.111
21 fit_09_KOR.out  KOR   09 OPD SES_B  0.011 0.062 0.858      -0.111 0.133
22 fit_09_LIE.out  LIE   09 OPD SES_B  0.062 0.067 0.358      -0.070 0.193
23 fit_09_LVA.out  LVA   09 OPD SES_B -0.049 0.068 0.468      -0.183 0.084
24 fit_09_MEX.out  MEX   09 OPD SES_B  0.067 0.059 0.257      -0.049 0.184
25 fit_09_NLD.out  NLD   09 OPD SES_B  0.150 0.086 0.081      -0.018 0.318
26 fit_09_NOR.out  NOR   09 OPD SES_B  0.405 0.157 0.010 *     0.096 0.713
27 fit_09_NZL.out  NZL   09 OPD SES_B  0.346 0.059 0.000 ***   0.231 0.461
28 fit_09_POL.out  POL   09 OPD SES_B  0.157 0.060 0.009 **    0.038 0.275
29 fit_09_PRY.out  PRY   09 OPD SES_B  0.352 0.044 0.000 ***   0.265 0.439
30 fit_09_RUS.out  RUS   09 OPD SES_B  0.019 0.138 0.889      -0.252 0.290
31 fit_09_SVK.out  SVK   09 OPD SES_B  0.053 0.048 0.271      -0.042 0.148
32 fit_09_SVN.out  SVN   09 OPD SES_B  0.057 0.084 0.495      -0.108 0.223
33 fit_09_SWE.out  SWE   09 OPD SES_B  0.305 0.076 0.000 ***   0.155 0.455
34 fit_09_THA.out  THA   09 OPD SES_B  0.130 0.070 0.065      -0.008 0.268
35 fit_09_TWN.out  TWN   09 OPD SES_B  0.204 0.053 0.000 ***   0.099 0.308
36 fit_16_BFL.out  BFL   16 OPD SES_B  0.109 0.082 0.183      -0.052 0.270
37 fit_16_BGR.out  BGR   16 OPD SES_B  0.228 0.064 0.000 ***   0.103 0.353
38 fit_16_CHL.out  CHL   16 OPD SES_B  0.134 0.044 0.002 **    0.047 0.220
39 fit_16_COL.out  COL   16 OPD SES_B  0.320 0.080 0.000 ***   0.164 0.476
40 fit_16_DNK.out  DNK   16 OPD SES_B  0.405 0.074 0.000 ***   0.260 0.549
41 fit_16_DNW.out  DNW   16 OPD SES_B  0.265 0.078 0.001 **    0.112 0.418
42 fit_16_DOM.out  DOM   16 OPD SES_B  0.268 0.088 0.002 **    0.096 0.439
43 fit_16_EST.out  EST   16 OPD SES_B  0.142 0.059 0.016 *     0.027 0.257
44 fit_16_FIN.out  FIN   16 OPD SES_B  0.158 0.053 0.003 **    0.054 0.262
45 fit_16_HKG.out  HKG   16 OPD SES_B  0.123 0.079 0.117      -0.031 0.277
46 fit_16_HRV.out  HRV   16 OPD SES_B  0.075 0.052 0.149      -0.027 0.178
47 fit_16_ITA.out  ITA   16 OPD SES_B  0.141 0.069 0.040 *     0.007 0.276
48 fit_16_KOR.out  KOR   16 OPD SES_B  0.156 0.156 0.316      -0.149 0.462
49 fit_16_LTU.out  LTU   16 OPD SES_B -0.118 0.076 0.118      -0.266 0.030
50 fit_16_LVA.out  LVA   16 OPD SES_B -0.052 0.052 0.313      -0.154 0.050
51 fit_16_MEX.out  MEX   16 OPD SES_B  0.083 0.042 0.049 *     0.000 0.166
52 fit_16_MLT.out  MLT   16 OPD SES_B  0.282 0.066 0.000 ***   0.152 0.412
53 fit_16_NLD.out  NLD   16 OPD SES_B  0.247 0.048 0.000 ***   0.152 0.342
54 fit_16_NOR.out  NOR   16 OPD SES_B  0.164 0.162 0.312      -0.154 0.482
55 fit_16_PER.out  PER   16 OPD SES_B  0.223 0.060 0.000 ***   0.105 0.340
56 fit_16_RUS.out  RUS   16 OPD SES_B -0.044 0.079 0.574      -0.198 0.110
57 fit_16_SVN.out  SVN   16 OPD SES_B  0.021 0.071 0.762      -0.117 0.160
58 fit_16_SWE.out  SWE   16 OPD SES_B  0.257 0.064 0.000 ***   0.131 0.382
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.

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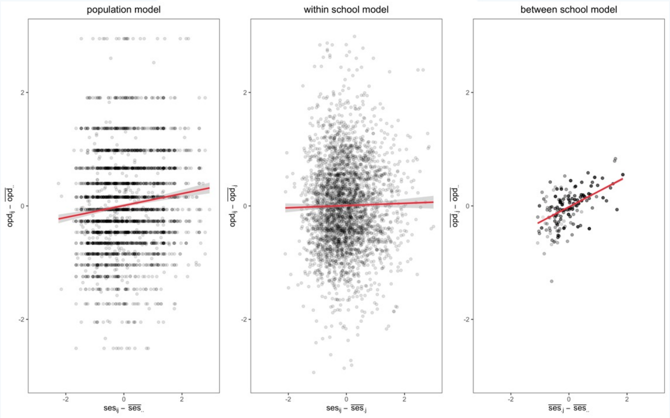
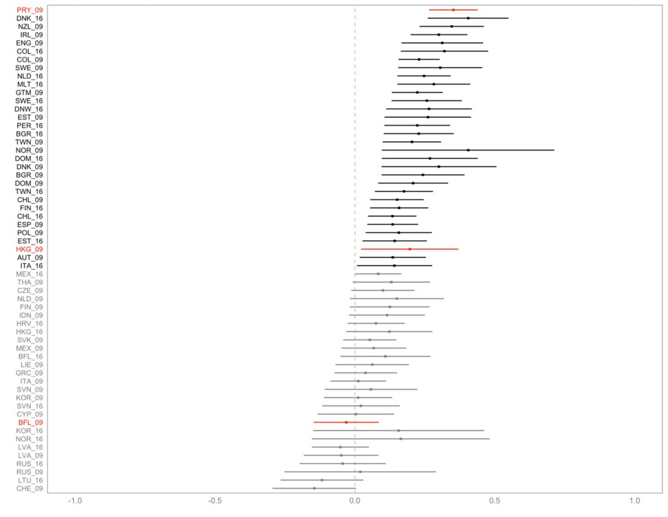
05_descriptives_plots.rmd

```
#-----------------------------------------------
# grid plot
#-----------------------------------------------

cowplot::plot_grid(p1, p2, p3, ncol=3)

#-----------------------------------------------
# save plot
#-----------------------------------------------

ggsave(paste0(plot_folder,file_text,'.png'),
     plot   = last_plot(),
     width  = 16,
     height = 10,
     units  = 'cm',
     dpi    = 400,
     scale  = 2)

#-----------------------------------------------
# display plot
#-----------------------------------------------

return(cowplot::plot_grid(p1, p2, p3, ncol=3))

}


#-----------------------------------------------
# list of countries
#-----------------------------------------------

dplyr::count(opd_09, COUNTRY) %>%
knitr::kable(.)

dplyr::count(opd_16, COUNTRY) %>%
knitr::kable(.)


```

Selected Plot

```{r echo=FALSE}

#------------------------------------------------------------------------------
# make grid plot
#------------------------------------------------------------------------------


plot_effects(data = opd_09, country = 'PRY', 'pry_2009')
plot_effects(data = opd_09, country = 'HKG', 'hkg_2009')
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
    - Auditable
    - Precise
    - Collaborative

Muchas gracias!

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López, N, MSSc.
Treviño, E., PhD

https://github.com/dacarras/cies_2021_opd