Socioeconomic Status and Child Psychopathology: A Meta-Analysis of Population-Based Studies. Appendix B: Analysis Code

Abstract

This document provides supplemental text to the main manuscript. It presents our statistical code, formulas, and background information necessary for transparency and replication, including supplemental analyses and figures.

Contents

1 Analysis Code and Output

2 Session Info

This describes the R environment in which the analysis was run:

R version 3.5.1 (2018-07-02)

Platform: x86_64-w64-mingw32/x64 (64-bit)

locale: *LC_COLLATE=English_United States.1252*, *LC_CTYPE=English_United States.1252*, *LC_MONETARY=English_United States.1252*, *LC_NUMERIC=C* and *LC_TIME=English_United States.1252*

attached base packages: *grid*, *stats*, *graphics*, *grDevices*, *utils*, *datasets*, *methods* and *base*

other attached packages: *forestplot(v.1.7.2)*, *checkmate(v.1.8.5)*, *magrittr(v.1.5)*, *dplyr(v.0.8.3)*, *esc(v.0.4.1)*, *knitr(v.1.26)*, *metafor(v.2.0-0)*, *Matrix(v.1.2-17)*, *Hmisc(v.4.3-0)*, *ggplot2(v.3.2.1)*, *Formula(v.1.2-3)*, *survival(v.3.1-7)*, *lattice(v.0.20-38)* and *pander(v.0.6.3)*

loaded via a namespace (and not attached): *stringdist(v.0.9.5.2)*, *Rcpp(v.1.0.2)*, *tidyr(v.1.0.0)*, *assertthat(v.0.2.0)*, *zeallot(v.0.1.0)*, *digest(v.0.6.18)*, *R6(v.2.3.0)*, *backports(v.1.1.2)*, *acepack(v.1.4.1)*, *evaluate(v.0.14)*, *pillar(v.1.4.2)*, *rlang(v.0.4.1)*, *lazyeval(v.0.2.1)*, *rstudioapi(v.0.8)*, *data.table(v.1.12.6)*, *rpart(v.4.1-13)*, *rmarkdown(v.1.17)*, *splines(v.3.5.1)*, *readr(v.1.1.1)*, *stringr(v.1.3.1)*, *foreign(v.0.8-71)*, *htmlwidgets(v.1.5.1)*, *munsell(v.0.5.0)*, *broom(v.0.5.0)*, *compiler(v.3.5.1)*, *xfun(v.0.11)*, *pkgconfig(v.2.0.2)*, *base64enc(v.0.1-3)*, *htmltools(v.0.4.0)*, *nnet(v.7.3-12)*, *insight(v.0.8.3)*, *tidyselect(v.0.2.5)*, *tibble(v.2.1.3)*, *gridExtra(v.2.3)*, *htmlTable(v.1.12)*, *crayon(v.1.3.4)*, *withr(v.2.1.2)*, *sjmisc(v.2.7.5)*, *nlme(v.3.1-137)*, *gtable(v.0.2.0)*, *lifecycle(v.0.1.0)*, *scales(v.1.0.0)*, *stringi(v.1.2.4)*, *latticeExtra(v.0.6-28)*, *vctrs(v.0.2.0)*, *sjlabelled(v.1.1.1)*, *RColorBrewer(v.1.1-2)*, *tools(v.3.5.1)*, *forcats(v.0.3.0)*, *glue(v.1.3.0)*, *purrr(v.0.3.3)*, *hms(v.0.4.2)*, *parallel(v.3.5.1)*, *yaml(v.2.2.0)*, *colorspace(v.1.3-2)*, *cluster(v.2.0.7-1)* and *haven(v.2.2.0)*

3 Variables

Descriptions of variables used in analysis:

Variable	Label
study.ID [labelled, factor]	ID of study (dataset)
paper.ID [labelled, factor]	ID of paper
cite [labelled, character]	Citation
location [labelled, character]	Location of effect in text
n [labelled, integer]	
ageMean [labelled, numeric]	mean age of participants
whitePerc [labelled, numeric]	Percent of sample reported white
IV [labelled, factor]	SES Variable Type

Variable	Label
sesOper [labelled, character]	Operationalization of SES
DV [labelled, factor]	Psychopathology Variable Type
psychOper [labelled, character]	Operationalization of Psych
measure [labelled, factor]	Who reported the information and by what means
Externalizing [labelled, logical]	Is the Outcome externalizing?
Continuous [labelled, logical]	Is the outcome continuous?
adjusted [labelled, logical]	Was the effect adjusted for covariates
weighted [labelled, logical]	Was the effect calculated with sample weighting applied
wave [labelled, character]	what wave of the study was the effect from
date [labelled, numeric]	Approx date of data collection
povFocus [labelled, logical]	was poverty a major focus of the publication
OR [labelled, numeric]	raw odds ratio
p [labelled, numeric]	p value
SE [labelled, numeric]	standard error
ci.L [labelled, numeric]	2.5 percent confidence interval
ci.H [labelled, numeric]	97.5 percent confidence interval
r [labelled, numeric]	bivariate correlation
beta [labelled, numeric]	standardized coefficient
ai [labelled, numeric]	n with poverty and psychopathology
bi [labelled, numeric]	n without poverty but pathology
ci [labelled, numeric]	n with poverty without pathology
di [labelled, numeric]	n without poverty or pathology
m1ia [labelled, numeric]	mean psychopathology of poverty group
sd1ia [labelled, numeric]	sd psychopathology of poverty group
n1ia [labelled, numeric]	n of poverty group
m2ia [labelled, numeric]	mean psychopathology of no-poverty group
sd2ia [labelled, numeric]	sd psychopathology of no-poverty group
n2ia [labelled, numeric]	n of no-poverty group
m1ib [labelled, numeric]	mean SES of dx group
sd1ib [labelled, numeric]	sd SES of dx group
n1ib [labelled, integer]	n of dx group
m2ib [labelled, numeric]	mean SES of dx- group

Variable	Label
sd2ib [labelled, numeric]	sd SES of dx- group
n2ib [labelled, integer]	n of dx- group
rr [labelled, numeric]	raw risk ratio
f [labelled, numeric]	f score

4 Sources

Location of effects pulled for meta-analysis:

efid	study.ID	cite	location	IV	DV
1	CDP	Lansford et al., 2006	table 3; pg 23	Hollingshead	Externalizing symptoms
2	CDP	Lansford et al., 2006	table 3; pg 23	Hollingshead	Internalizing symptoms
3	GSM	Costello et al., 1996*	calc	Poverty Status (poverty line)	Externalizing symptoms
4	GSM	Costello et al., 1996*	calc	Parental Ed	Externalizing symptoms
5	GSM	Costello et al., 1996*	calc	Poverty Status (poverty line)	ADHD
6	GSM	Costello et al., 1996*	calc	Poverty Status (poverty line)	PTSD
7	GSM	Costello et al., 1996*	calc	Poverty Status (poverty line)	Depr.
8	GSM	Costello et al., 1996*	calc	Poverty Status (poverty line)	Anx.
9	GSM	Costello et al., 1996*	calc	Poverty Status (poverty line)	Disruptive behavior disorders (ODD/CONDUCT)
10	GSM	Costello et al., 1996*	calc	Parental Ed	ADHD
11	GSM	Costello et al., 1996*	calc	Parental Ed	PTSD
12	GSM	Costello et al., 1996*	calc	Parental Ed	Depr.
13	GSM	Costello et al., 1996*	calc	Parental Ed	Anx.
14	GSM	Costello et al., 1996*	calc	Parental Ed	Disruptive behavior disorders (ODD/CONDUCT)
15	MECA	Lahey et al., 1996*	calc	Poverty Status (poverty line)	ADHD
16	MECA	Lahey et al., 1996*	calc	Family Income	ADHD

efid	study.ID	cite	location	IV	DV
17	MECA	Lahey et al., 1996*	calc	Parental Ed	ADHD
18	MECA	Lahey et al., 1996*	calc	Receipt of Public Assistance	ADHD
19	MECA	Lahey et al., 1996*	calc	Poverty Status (poverty line)	Depr.
20	MECA	Lahey et al., 1996*	calc	Family Income	Depr.
21	MECA	Lahey et al., 1996*	calc	Parental Ed	Depr.
22	MECA	Lahey et al., 1996*	calc	Receipt of Public Assistance	Depr.
23	MECA	Lahey et al., 1996*	calc	Poverty Status (poverty line)	Anx.
24	MECA	Lahey et al., 1996*	calc	Family Income	Anx.
25	MECA	Lahey et al., 1996*	calc	Parental Ed	Anx.
26	MECA	Lahey et al., 1996*	calc	Receipt of Public Assistance	Anx.
27	MECA	Lahey et al., 1996*	calc	Poverty Status (poverty line)	Disruptive behavior disorders (ODD/CONDUCT)
28	MECA	Lahey et al., 1996*	calc	Family Income	Disruptive behavior disorders (ODD/CONDUCT)
29	MECA	Lahey et al., 1996*	calc	Parental Ed	Disruptive behavior disorders (ODD/CONDUCT)
30	MECA	Lahey et al., 1996*	calc	Receipt of Public Assistance	Disruptive behavior disorders (ODD/CONDUCT)
31	NCSA	McLaughlin et al., 2013	Table S5	Family Income	PTSD
32	NCSA	McLaughlin et al., 2013	Table S5	Parental Ed	PTSD
33	NCSA	Kessler et al., 2014	Table 1	Parental Ed	ADHD
34	NCSA	McLaughlin et al., 2012	table 2	Poverty Status (poverty line)	Depr.
35	NCSA	McLaughlin et al., 2012	table 2	Poverty Status (poverty line)	Anx.
36	NCSA	McLaughlin et al., 2012	table 2	Poverty Status (poverty line)	Disruptive behavior disorders (ODD/CONDUCT)

efid	study.ID	cite	location	IV	DV
37	NCSA	McLaughlin et al., 2012	table 2	Parental Ed	Depr.
38	NCSA	McLaughlin et al., 2012	table 2	Parental Ed	Anx.
39	NCSA	McLaughlin et al., 2012	table 2	Parental Ed	Disruptive behavior disorders (ODD/CONDUCT)
40	NCSA	McLaughlin et al., 2012	table 2	Subjective SES	Depr.
41	NCSA	McLaughlin et al., 2012	table 2	Subjective SES	Anx.
42	NCSA	McLaughlin et al., 2012	table 2	Subjective SES	Disruptive behavior disorders (ODD/CONDUCT)
43	NHANES	Braun et al., 2008	4 (table 2)	Poverty Status (poverty line)	Disruptive behavior disorders (ODD/CONDUCT)
44	NHANES	Byrd, et. al., 2013	Table 1	Poverty Status (poverty line)	ADHD
45	NHANES	Merikangas et al., 2012	Table 1	Poverty Status (poverty line)	Depr.
46	PGS	Keenan et al., 2010	pg 4	Receipt of Public Assistance	Disruptive behavior disorders (ODD/CONDUCT)
47	PGS	Hipwell et al., 2011	pg 4	Poverty Status (poverty line)	Disruptive behavior disorders (ODD/CONDUCT)
48	PGS	Hipwell et al., 2011	pg 4	Poverty Status (poverty line)	Depr.
49	PHDCN	Xue et al., 2005	Table 3	Parental Ed	Internalizing symptoms
50	PHDCN	Xue et al., 2005	Table 3	Family Income	Internalizing symptoms
51	PHDCN	Xue et al., 2005	Table 3	Receipt of Public Assistance	Internalizing symptoms
52	PHDCN	Xue et al., 2005	Table 3	Parental Ed	Internalizing symptoms
53	PHDCN	Xue et al., 2005	Table 3	Family Income	Internalizing symptoms
54	PHDCN	Xue et al., 2005	Table 3	Receipt of Public Assistance	Internalizing symptoms
55	PHDCN	Slopen et al., 2010	448 text	Poverty Status (poverty line)	Internalizing symptoms
56	PHDCN	Slopen et al., 2010	448 text	Poverty Status (poverty line)	Externalizing symptoms

efid	study.ID	cite	location	IV	DV
57	PHDCN	Zhang, 2012	pg 42 (table 4)	Family Income	Internalizing symptoms
58	PHDCN	Zhang, 2012	pg 42 (table 4)	Family Income	Externalizing symptoms
59	PYS	Maughan et al., 2003	pg 5	Hollingshead	Depr.
60	PYS.m	Loeber et al., 1998	170	Hollingshead	ADHD
61	PYS.y	Loeber et al., 1998	170	Receipt of Public Assistance	ADHD
62	PYS.m	Loeber et al., 1998	172	Hollingshead	Disruptive behavior disorders (ODD/CONDUCT)
63	PYS.o	Loeber et al., 1998	172	Hollingshead	Disruptive behavior disorders (ODD/CONDUCT)
64	PYS.y	Loeber et al., 1998	172	Receipt of Public Assistance	Disruptive behavior disorders (ODD/CONDUCT)
65	PYS.m	Loeber et al., 1998	172	Receipt of Public Assistance	Disruptive behavior disorders (ODD/CONDUCT)
66	PYS.o	Loeber et al., 1998	172	Receipt of Public Assistance	Disruptive behavior disorders (ODD/CONDUCT)
67	PYS.y	Loeber et al., 1998	172	Parental Ed	Disruptive behavior disorders (ODD/CONDUCT)
68	PYS.o	Loeber et al., 1998	172	Parental Ed	Disruptive behavior disorders (ODD/CONDUCT)
69	PYS.y	Loeber et al., 1998	205	Hollingshead	Depr.
70	PYS.y	Loeber et al., 1998	205	Receipt of Public Assistance	Depr.
71	PYS.m	Loeber et al., 1998	205	Receipt of Public Assistance	Depr.
72	PYS.y	Loeber et al., 1998	205	Parental Ed	Depr.
73	CIC	Cohen & Hesselbart, 1993*		Family Income	ADHD
74	CIC	Cohen & Hesselbart, 1993*		Poverty Status (poverty line)	ADHD

efid	study.ID	cite	location	IV	DV
75	CIC	Cohen & Hesselbart, 1993*		Parental Ed	ADHD
76	CIC	Cohen & Hesselbart, 1993*		Receipt of Public Assistance	ADHD
77	CIC	Cohen & Hesselbart, 1993*		Family Income	Depr.
78	CIC	Cohen & Hesselbart, 1993*		Poverty Status (poverty line)	Depr.
79	CIC	Cohen & Hesselbart, 1993*		Parental Ed	Depr.
80	CIC	Cohen & Hesselbart, 1993*		Receipt of Public Assistance	Depr.
81	CIC	Cohen & Hesselbart, 1993*		Family Income	Anx.
82	CIC	Cohen & Hesselbart, 1993*		Poverty Status (poverty line)	Anx.
83	CIC	Cohen & Hesselbart, 1993*		Parental Ed	Anx.
84	CIC	Cohen & Hesselbart, 1993*		Receipt of Public Assistance	Anx.
85	CIC	Cohen & Hesselbart, 1993*		Family Income	Disruptive behavior disorders (ODD/CONDUCT)
86	CIC	Cohen & Hesselbart, 1993*		Poverty Status (poverty line)	Disruptive behavior disorders (ODD/CONDUCT)
87	CIC	Cohen & Hesselbart, 1993*		Parental Ed	Disruptive behavior disorders (ODD/CONDUCT)
88	CIC	Cohen & Hesselbart, 1993*		Receipt of Public Assistance	Disruptive behavior disorders (ODD/CONDUCT)
89	CIC	Cohen & Hesselbart, 1993*		Family Income	Internalizing symptoms
90	CIC	Cohen & Hesselbart, 1993*		Poverty Status (poverty line)	Internalizing symptoms

efid	study.ID	cite	location	IV	DV
91	CIC	Cohen & Hesselbart, 1993*		Parental Ed	Internalizing symptoms
92	CIC	Cohen & Hesselbart, 1993*		Receipt of Public Assistance	Internalizing symptoms
93	CIC	Cohen & Hesselbart, 1993*		Family Income	Externalizing symptoms
94	CIC	Cohen & Hesselbart, 1993*		Poverty Status (poverty line)	Externalizing symptoms
95	CIC	Cohen & Hesselbart, 1993*		Parental Ed	Externalizing symptoms
96	CIC	Cohen & Hesselbart, 1993*		Receipt of Public Assistance	Externalizing symptoms
97	FF	Waller, 2001*		Family Income	Externalizing symptoms
98	FF	Waller, 2001*		Poverty Status (poverty line)	Externalizing symptoms
99	FF	Waller, 2001*		Parental Ed	Externalizing symptoms
100	FF	Waller, 2001*		Receipt of Public Assistance	Externalizing symptoms
101	FF	Waller, 2001*		Family Income	Externalizing symptoms2
102	FF	Waller, 2001*		Poverty Status (poverty line)	Externalizing symptoms2
103	FF	Waller, 2001*		Parental Ed	Externalizing symptoms2
104	FF	Waller, 2001*		Receipt of Public Assistance	Externalizing symptoms2
105	FF	Waller, 2001*		Family Income	Internalizing symptoms2
106	FF	Waller, 2001*		Poverty Status (poverty line)	Internalizing symptoms2
107	FF	Waller, 2001*		Parental Ed	Internalizing symptoms2
108	FF	Waller, 2001*		Receipt of Public Assistance	Internalizing symptoms2
109	NSPC	McClure, 2007	Table 8	Hollingshead	Externalizing symptoms
110	NSPC	McClure, 2007	Table 7	Hollingshead	Internalizing symptoms
111	NSPC	McClure, 2007	Table 8	Receipt of Public Assistance	Externalizing symptoms
112	NSPC	McClure, 2007	Table 7	Receipt of Public Assistance	Internalizing symptoms

efid	study.ID	cite	location	IV	DV
113	PSID.CDS2	Panel Study of Income Dynamics, 2020*		Family Income	Depr.
114	PSID.CDS2	Panel Study of Income Dynamics, 2020*		Poverty Status (poverty line)	Depr.
115	PSID.CDS2	Panel Study of Income Dynamics, 2020*		Parental Ed	Depr.
116	PSID.CDS2	Panel Study of Income Dynamics, 2020*		Receipt of Public Assistance	Depr.
117	PSID.CDS2014	Panel Study of Income Dynamics, 2020*		Family Income	Depr.
118	PSID.CDS2014	Panel Study of Income Dynamics, 2020*		Poverty Status (poverty line)	Depr.
119	PSID.CDS2014	Panel Study of Income Dynamics, 2020*		Parental Ed	Depr.
120	PSID.CDS2014	Panel Study of Income Dynamics, 2020*		Receipt of Public Assistance	Depr.

*: Data provided by study authors.

5 Sample Description Generation

```
#we should have one column with sample size per study ID. Specified manually:
agedf<-esdf[c(1,3,17,31,45,46,55,59,74,104,109,113,117),c("study.ID","n","ageMin","ageMax","ageMean",
                                                             "whitePerc","blackPerc","latPerc","femalePerc")]
with(agedf,weighted.mean(ageMean,n))
```

```
## [1] 12.35228
```

```
with(agedf,weighted.mean(whitePerc,n))
```

```
## [1] 0.508022
```

```
with(agedf,weighted.mean(blackPerc,n))
```

```
## [1] 0.2746456
```

```r
with(agedf,weighted.mean(latPerc,n,na.rm=TRUE))
```

```
## [1] 0.2120555
```

```r
with(agedf,weighted.mean(femalePerc,n,na.rm=TRUE))
```

```
## [1] 0.5035472
```

The combined sample represented 26715 children across the contiguous United States. The sample was 50.3547196% female, and 50.8022033% Non-Hispanic White. The sample represented children aged 3-19.3333333, with an average age of 12.3522782 years. Of the effects entered, 52.5% used combined methods (multiple reporters) to assess psychopathology, and -12.3333333% were unadjusted for covariates. Most associations (85%) were not taken from papers in which the association of family SES on psychopathology was a primary focus of the work.

6 Effect Size Calculations

We used a strategy from Borenstein (2009) to consolidate different sources of effects printed in the literature. Dichotomous SES to dichotomous psychopathology effects are converted in to log odds ratio. Continuous relationships are converted to z-transformed r. Continuous SES to dichotomous psychopathology and Dichotomous SES to continuous psychopathology effects are converted in to standard mean difference (d) and from there to Hedge's g (a bias corrected measure of standard mean difference).

Later, we will convert between these effect types for specific analyses.

6.1 OR calculation

First we will calculate log odds ratios. Data convertible to OR was given in one of two formats: 2x2 tables or odds ratio.

6.1.1 2x2 tables

Log OR can be calculated for these effects using metafor::escalc. We will add .01 to 0 cells (this allows inclusion of studies which had no cases of psychopathology in the low SES group with a variance sufficiently large that they will not bias the finding, and sufficiently small that the effect will mostly fit on the plot).

```r
esdf<-escalc(ai=ai,bi=bi,ci=ci,di=di,var.names=c("lOR","lOR.v"),measure="OR",data=esdf,append=TRUE,replace=FALSE,add=.01)
```

This provides the following values:

	n	sesOper	psychOper	ai	bi	ci	di	lOR	lOR.v
5	1420	< Poverty Line	CAPA DSM-3	6	15	327	1025	0.21	0.24
6	1420	< Poverty Line	CAPA DSM-3	0	0.42	313	998	-2.6	102
7	1420	< Poverty Line	CAPA DSM-3	0.44	2.2	333	1038	-0.46	2.7

	n	sesOper	psychOper	ai	bi	ci	di	lOR	lOR.v
8	1420	< Poverty Line	CAPA DSM-3	30	39	303	1002	0.96	0.063
9	1420	< Poverty Line	CAPA DSM-3	44	48	289	992	1.1	0.048
10	1420	< HS ed.	CAPA DSM-3	0.44	21	7.1	1384	1.4	2.5
11	1420	< HS ed.	CAPA DSM-3	0	0.42	6.2	1337	1.6	102
12	1420	< HS ed.	CAPA DSM-3	0	2.6	7.6	1402	-0.35	101
13	1420	< HS ed.	CAPA DSM-3	0.44	70	7.1	1334	0.15	2.4
14	1420	< HS ed.	CAPA DSM-3	1.3	93	6.2	1311	1.1	0.93
15	970	< Poverty Line		7	53	125	785	-0.19	0.17
17	984	< HS ed.		3	58	51	872	-0.12	0.37
18	290	"on public assistance (welfare)"		5	8	57	220	0.88	0.35
19	970	< Poverty Line		11	51	121	787	0.34	0.12
21	984	< HS ed.		4	58	50	872	0.18	0.29
22	290	"on public assistance (welfare)"		8	19	54	209	0.49	0.2
23	970	< Poverty Line		36	168	96	670	0.4	0.046
25	984	< HS ed.		15	189	39	741	0.41	0.099
26	290	"on public assistance (welfare)"		16	45	46	183	0.35	0.11
27	970	< Poverty Line		20	75	112	763	0.6	0.074
29	984	< HS ed.		7	88	47	842	0.35	0.18
30	290	"on public assistance (welfare)"		16	18	46	210	1.4	0.14
43	3081	PIR <1 (higher cells summed)	DISC CD crit. In 12 months	25	40	875	2090	0.4	0.067
44	3081	< Poverty Line	DISC Parent Interview	160	313	703	1759	0.24	0.011
45	4150	< Poverty Line	DISC Adolescent (16-19) or combined DISC (12-15)	47	89	1364	2650	0.015	0.034
46	2393	public assistance any year	Met conduct disorder any year	440	120	939	894	1.3	0.013
55	2810	< Poverty Line	Int >90 percentile t-score	627	427	2183	2383	0.47	0.0048
56	2810	< Poverty Line	Ext >90 percentile t-score	289	160	2521	2650	0.64	0.01
74	776	< Poverty Line	ADHD DISC crit and >1SD symptoms	26	67	96	582	0.86	0.066

	n	sesOper	psychOper	ai	bi	ci	di	lOR	lOR.v
75	776	max parent years edu<12	ADHD DISC crit and >1SD symptoms	14	79	64	619	0.54	0.1
76	776	Welfare	ADHD DISC crit and >1SD symptoms	11	81	27	644	1.2	0.14
78	776	< Poverty Line	Depression DISC crit and >1SD symptoms	11	14	111	635	1.5	0.17
79	776	max parent years edu<12	Depression DISC crit and >1SD symptoms	4	21	74	677	0.56	0.31
80	776	Welfare	Depression DISC crit and >1SD symptoms	4	21	34	704	1.4	0.33
82	776	< Poverty Line	so phobia, overanxous, or separation anx DISC crit and >1SD symptoms	42	132	80	517	0.72	0.046
83	776	max parent years edu<12	so phobia, overanxous, or separation anx DISC crit and >1SD symptoms	28	148	50	550	0.73	0.064
84	776	Welfare	so phobia, overanxous, or separation anx DISC crit and >1SD symptoms	17	156	21	569	1.1	0.11
86	776	< Poverty Line	add, opd or cd DISC crit and >1SD symptoms	52	126	70	523	1.1	0.043
87	776	max parent years edu<12	add, opd or cd DISC crit and >1SD symptoms	30	150	48	548	0.83	0.063
88	776	Welfare	add, opd or cd DISC crit and >1SD symptoms	16	161	22	564	0.94	0.12

6.1.2 Raw OR

In the case of provided OR's, we just need to convert confidence intervals and p values to SE and log transform. Formulas for calculating SE from CI and p from cochrane reviews (Green & Higgins, 2011; section 7.7.7). First, confidence intervals and ORs are log transformed. Then formulas can be used to calculate SE from CI or a p value:

$$\sigma = \frac{CI_{high} - CI_{low}}{3.92}$$

When a p value is provided, the p value should be converted first to a z score using a standard table. Then:

$$\sigma = \frac{lOR}{Z(p)}$$

p calculated SE's will be approximate and conservative, since we are often working off a thresholded value (e.g. when the publication provided p<.05).

```
esdf[!is.na(esdf$OR)&!is.na(esdf$ci.L),"SE"]<-with(esdf[!is.na(esdf$OR)&!is.na(esdf$ci.L),],
    (log(ci.H)-log(ci.L))/3.92)

esdf[!is.na(esdf$OR)&!is.na(esdf$p),"SE"]<-with(esdf[!is.na(esdf$OR)&!is.na(esdf$p),],
    abs(log(OR)/qnorm(p)))

esdf[!is.na(esdf$OR),]<-escalc(data=esdf[!is.na(esdf$OR),],
             measure="OR",
             yi=log(OR),
             sei=SE,
             var.names=c("lOR","lOR.v"),
             append=TRUE,
             replace=TRUE)
```

This outputs the following:

	n	sesOper	psychOper	OR	SE	p	ci.L	ci.H	lOR	lOR.v
31	6483	< 3*Poverty Line	CIDI combined interview PTSD diag	1.3	0.23	NA	0.8	2	0.26	0.055
32	6483	No college	CIDI combined interview PTSD diag	1	0.18	NA	0.7	1.4	0	0.031
33	6483	< HS ed.	CIDI combined interview ADHD diag	1.7	0.22	NA	1.1	2.6	0.53	0.048
34	6483	< 1.5*Poverty		1	0.25	NA	0.6	1.6	0	0.063
35	6483	< 1.5*Poverty		1.3	0.15	NA	1	1.8	0.26	0.022
36	6483	< 1.5*Poverty	DBD diagnosis	1.2	0.19	NA	0.8	1.7	0.18	0.037
37	6483	< HS ed.		1	0.21	NA	0.7	1.6	0	0.044
38	6483	< HS ed.		1.7	0.13	NA	1.3	2.2	0.53	0.018
39	6483	< HS ed.	DBD diagnosis	1.5	0.25	NA	0.9	2.4	0.41	0.063

	n	sesOper	psychOper	OR	SE	p	ci.L	ci.H	lOR	lOR.v
40	6483	Community Ladder		0.8	0.034	NA	0.7	0.8	-0.22	0.0012
41	6483	Community Ladder		0.8	0.03	NA	0.8	0.9	-0.22	9e-04
42	6483	Community Ladder	Behavior Disorder	0.7	0.034	NA	0.7	0.8	-0.36	0.0012
59	1509	low SES (Hollingshead=1)	thresholded SMFQ value	1.7	0.2	NA	1.2	2.6	0.53	0.039
60	508	low SES (Hollingshead=1)	25% threshold of ADHD, high overlap with diagnosis	1.6	0.29	0.05	NA	NA	0.47	0.082
61	503	Welfare	25% threshold of ADHD, high overlap with diagnosis	1.7	0.23	0.01	NA	NA	0.53	0.052
62	508	low SES (Hollingshead=1)	25% threshold of Conduct, moderate overlap with diagnosis	2	0.3	0.01	NA	NA	0.69	0.089
63	506	low SES (Hollingshead=1)	25% threshold of Conduct, moderate overlap with diagnosis	1.5	0.25	0.05	NA	NA	0.41	0.061
64	503	Welfare	25% threshold of Conduct, moderate overlap with diagnosis	2.2	0.26	0.001	NA	NA	0.79	0.065
65	508	Welfare	25% threshold of Conduct, moderate overlap with diagnosis	1.7	0.32	0.05	NA	NA	0.53	0.1
66	506	Welfare	25% threshold of Conduct, moderate overlap with diagnosis	2.3	0.27	0.001	NA	NA	0.83	0.073
67	503	< HS ed.	25% threshold of Conduct, moderate overlap with diagnosis. Mothers ed <12th grade	1.5	0.25	0.05	NA	NA	0.41	0.061

	n	sesOper	psychOper	OR	SE	p	ci.L	ci.H	lOR	lOR.v
68	506	< HS ed.	25% threshold of Conduct, moderate overlap with diagnosis.	2.2	0.26	0.001	NA	NA	0.79	0.065
69	503	low SES (Hollingshead=1)	total score on SMF, but how did they get an OR?	1.6	0.29	0.05	NA	NA	0.47	0.082
70	503	Welfare	total score on SMF, but how did they get an OR?	1.9	0.28	0.01	NA	NA	0.64	0.076
71	508	Welfare	total score on SMF, but how did they get an OR?	1.7	0.32	0.05	NA	NA	0.53	0.1
72	503	< HS ed.	total score on SMF, but how did they get an OR?	1.5	0.25	0.05	NA	NA	0.41	0.061

6.2 g calculation

6.2.1 Mean and standard deviation

This is a straightforward calculation from metafor's escalc function. In our data frame, the relevant variables are as follows:

m1ia	sd1ia	n1ia	m2ia	sd2ia	n2ia
mean psychopathology of poverty group	sd psychopathology of poverty group	n of poverty group	mean psychopathology of no-poverty group	sd psychopathology of no-poverty group	n of no-poverty group

```
esdf$g<-NA
esdf$g.v<-NA
esdf[!is.na(esdf$sd1ia),]<-escalc(data=esdf[!is.na(esdf$sd1ia),],
             measure="SMD",
             m1i=m1ia,
             sd1i=sd1ia,
             n1i=n1ia,
             m2i=m2ia,
```

```
sd2i=sd2ia,
n2i=n2ia,
var.names=c("g","g.v"),
append=TRUE,
replace=TRUE)
```

	n	sesOper	psychOper	m1ia	sd1ia	n1ia	m2ia	sd2ia	n2ia	g	g.v
3	1420	< Poverty Line	CBCL Problem Score	14	9.5	461	11	7.2	889	0.31	0.0033
4	1420	< HS ed.	CBCL Problem Score	13	5.5	20	12	7.8	1249	0.11	0.051
90	776	< Poverty Line	sum z score of DISC dep, sep anx, overanx, soc phob	1.2	3.7	122	-0.24	2.9	649	0.48	0.0099
91	776	max parent years edu<12	sum z score of DISC dep, sep anx, overanx, soc phob	1.2	3.6	78	-0.13	3	698	0.44	0.014
92	776	Welfare	sum z score of DISC dep, sep anx, overanx, soc phob	2	4	38	-0.1	3	725	0.69	0.028
94	776	< Poverty Line	sum z score of DISC add, conduct, odd	1	3	122	-0.2	2.4	649	0.48	0.0099
95	776	max parent years edu<12	sum z score of DISC add, conduct, odd	1.3	3.2	78	-0.15	2.4	698	0.58	0.014
96	776	Welfare	sum z score of DISC add, conduct, odd	1.2	3	38	-0.07	2.5	725	0.48	0.028
98	1589	< Poverty Line	Sum of CBCL Ext. items	11	6.6	561	9.4	5.4	1028	0.21	0.0028
99	1588	Less than HS Degree	Sum of CBCL Ext. items	10	6.7	257	9.8	5.7	1331	0.076	0.0046
100	1589	Received free food/Foodstamps	Sum of CBCL Ext. items	11	6.5	543	9.2	5.4	1046	0.3	0.0028

	n	sesOper	psychOper	m1ia	sd1ia	n1ia	m2ia	sd2ia	n2ia	g	g.v
102	2246	< Poverty Line	Sum of CBCL Ext. items	42	9	731	40	6	1515	0.33	0.0021
103	2259	Less than HS Degree	Sum of CBCL Ext. items	42	10	297	41	6.5	1962	0.25	0.0039
104	2282	Received free food/Foodstamps	Sum of CBCL Ext. items	44	6.6	214	41	7.2	2068	0.42	0.0052
106	2246	< Poverty Line	Sum of CBCL Int. items	39	7.5	731	36	4.7	1515	0.35	0.0021
107	2259	< HS ed.	Sum of CBCL Int. items	38	8.3	297	37	5.3	1962	0.24	0.0039
108	2282	Received free food/Foodstamps	Sum of CBCL Int. items	39	5.9	214	37	5.7	2068	0.4	0.0052
114	1455	< Poverty Line	Sum of CDI:S	2.9	3.2	178	2.7	3.3	1277	0.053	0.0064
115	1409	Less than HS Degree	Sum of CDI:S	2.9	3.3	221	2.7	3.2	1188	0.08	0.0054
116	1452	Received Foodstamps or TANF	Sum of CDI:S	3.1	3.3	156	2.7	3.3	1296	0.1	0.0072
118	1045	< Poverty Line	Sum of CDI:S	2.3	3.2	145	2.2	2.5	900	0.019	0.008
119	1064	Less than HS Degree	Sum of CDI:S	2.8	3.6	124	2.2	2.5	940	0.23	0.0092
120	1045	Received Foodstamps or TANF	Sum of CDI:S	2.4	3.1	212	2.2	2.5	833	0.08	0.0059

6.2.2 F test

2 effects provided an F score from an anova model comparing depression and disruptive symptoms in groups above/below the poverty line. We can most safely convert this effect to g, as it represents a dichotomous IV and continuous DV.

Calculation of SMD from an F test comparing two groups of unequal size is provided by David Wilson's website as a companion to Lipsey and Wilson's textbook. Implementation in R is provided by the 'esc' package (Lipsey & Wilson, 2000; Lüdecke, 2018).

```
esdf[!is.na(esdf$f),c("g","g.v")]<-as.data.frame(with(esdf[!is.na(esdf$f),],esc::esc_f(f=f,
                es.type="g",
                totaln=n,
                grp1n=n1ia,
                grp2n=n2ia)))[,c("es","var")]
```

	n	sesOper	psychOper	f	n1ia	n2ia	g	g.v
47	1232	< Poverty Line	CSI/ASI severity scores	40	419	813	0.36	0.0033
48	1232	< Poverty Line	CSI/ASI severity scores	13	419	813	0.21	0.0033

6.2.3 Continuous SES, Dichotomous Psychopathology

These are also calculated as g, but were entered using a separate set of variables to reflect the different interpretation. We also calculate point biserial correlation. However, calculating standard mean difference is more appropriate given the data we have, as converting to correlation makes more assumptions about the underlying data (Pustejovsky, 2014). We therefore use the standard mean difference in our analyses.

The relevant variables are:

m1ib	sd1ib	n1ib	m2ib	sd2ib	n2ib
mean SES of dx group	sd SES of dx group	n of dx group	mean SES of dx- group	sd SES of dx- group	n of dx- group

The interpretation is standard mean difference in SES with diagnosis.

```
esdf$rpb<-NA
esdf$rpb.v<-NA

#Point biserial corr. is calculated but not used.
esdf[!is.na(esdf$m1ib),]<-escalc(data=esdf[!is.na(esdf$m1ib),],
             measure="RPB",
             m1i=m1ib,
             sd1i=sd1ib,
             n1i=n1ib,
             m2i=m2ib,
             sd2i=sd2ib,
             n2i=n2ib,
             var.names=c("rpb","rpb.v"),
             vtype="ST",
             append=TRUE,
             replace=TRUE)

#Calculate SMD
esdf[!is.na(esdf$rpb),]<-escalc(data=esdf[!is.na(esdf$rpb),],
```

```
        measure="SMD",
        m1i=m1ib,
        sd1i=sd1ib,
        n1i=n1ib,
        m2i=m2ib,
        sd2i=sd2ib,
        n2i=n2ib,
        var.names=c("g","g.v"),
        append=TRUE,
        replace=TRUE)
```

This yields:

	n	sesOper	psychOper	m1ib	sd1ib	n1ib	m2ib	sd2ib	n2ib	g	g.v
16	970	Continuous $ Income		48233	30159	60	54896	33047	910	-0.2	0.018
20	970	Continuous $ Income		49362	35000	62	54833	32744	908	-0.17	0.017
24	970	Continuous $ Income		49823	33095	204	55725	32759	766	-0.18	0.0062
28	970	Continuous $ Income		43063	30016	95	55724	32977	875	-0.39	0.012
73	771	dollar income	ADHD DISC crit and >1SD symptoms	21352	15757	93	27440	15334	678	-0.4	0.012
77	771	dollar income	Depression DISC crit and >1SD symptoms	18405	14012	25	26984	15482	746	-0.56	0.042
81	771	dollar income	so phobia, overanxous, or separation anx DISC crit and >1SD symptoms	22212	14145	174	28016	15646	597	-0.38	0.0075
85	771	dollar income	add, opd or cd DISC crit and >1SD symptoms	21417	14955	178	28293	15323	593	-0.45	0.0074

6.3 Z transformed r (Zr) calculation

6.3.1 Regression coefficient (beta)

These effects are provided as β coefficients of SES variables in psychopathology models. There is some controversy about whether r values can safely be inputed from β in meta-analysis. In the case of an unadjusted model, β and r are equivalent, but assuming the coefficient is from a more complex model some bias is introduced. Peterson and Brown (2005) suggested the following formula:

$$r = .98\beta + .05\lambda$$

Where $\lambda = 1$ if β is nonnegative and $\lambda = 0$ if β is negative. In their paper, Peterson and Brown argue that this approach is superior to inputing the raw beta formula, an effect of zero, or leaving the effect out of the analysis. Since one beta weight was zero, we will assume that lambda should be 0 in that case so as not to inflate the indicator of no relationship.

However, Roth et al. (2018) conducted a set of simulation studies examining the efficiency of this method and found that, even in the best case, estimates of population are not more accurate than if these results are simply omitted. However, Roth et al. note that they did not perform simulations at low k values (as will be the case in many of our analyses). We will proceed to impute these values, but we additionally include a sensitivity analyses where they are omitted at the end of the document.

```
PetersonBetaToR<-function(beta) {
  lambda<-as.numeric(!beta<=0) # returns FALSE if beta is non-negative, which codes as 0.
  r=.98*beta+.05*lambda
  r
}

esdf[!is.na(esdf$beta)&is.na(esdf$r),"r"]<-sapply(esdf[!is.na(esdf$beta)&is.na(esdf$r),"beta"],PetersonBetaToR)
```

	n	IV	sesOper	DV	psychOper	beta	r
49	2805	Parental Ed	< HS ed.	Internalizing symptoms	continuous internalizing	0.097	0.15
50	2805	Family Income	Income to Needs	Internalizing symptoms	continuous internalizing	-0.048	-0.047
51	2805	Receipt of Public Assistance		Internalizing symptoms	continuous internalizing	0.042	0.091
52	2805	Parental Ed	< HS ed.	Internalizing symptoms	dichotomized internalizing	0.14	0.18
53	2805	Family Income	Income to Needs	Internalizing symptoms	dichotomized internalizing	-0.16	-0.16
54	2805	Receipt of Public Assistance		Internalizing symptoms	dichotomized internalizing	0.015	0.065

	n	IV	sesOper	DV	psychOper	beta	r
109	823	Hollingshead	SES stress' coded 1-3 where 3 represents a low hollingshead index	Externalizing symptoms	ACQ Externalizing Scale	0	0
110	823	Hollingshead	SES stress' coded 1-3 where 3 represents a low hollingshead index	Internalizing symptoms	ACQ Internalizing Scale	-0.04	-0.039
111	823	Receipt of Public Assistance	# of forms of Assistance	Externalizing symptoms	ACQ Externalizing Scale	0.1	0.15
112	823	Receipt of Public Assistance	# of forms of Assistance	Internalizing symptoms	ACQ Internalizing Scale	-0.01	-0.0098

These effects will now be included in the z to r transformation below.

6.3.2 r

This is also a straightforward calculation provided by escalc. At the sample sizes we are working with, the z value is not much different from r.

```
esdf$Zr<-NA
esdf$Zr.v<-NA
esdf[!is.na(esdf$r),]<-escalc(data=esdf[!is.na(esdf$r),],
                   measure="ZCOR",
                   ri=r,
                   ni=n,
                   var.names=c("Zr","Zr.v"),
                   append=TRUE,
                   replace=TRUE)
```

	n	sesOper	psychOper	beta	r	Zr	Zr.v
1	585	Continuous Hollingshead	TRF Problem Score	NA	-0.23	-0.23	0.0017
2	585	Continuous Hollingshead	TRF Problem Score	NA	-0.12	-0.12	0.0017
49	2805	< HS ed.	continuous internalizing	0.097	0.15	0.15	0.00036
50	2805	Income to Needs	continuous internalizing	-0.048	-0.047	-0.047	0.00036
51	2805		continuous internalizing	0.042	0.091	0.091	0.00036
52	2805	< HS ed.	dichotomized internalizing	0.14	0.18	0.19	0.00036

	n	sesOper	psychOper	beta	r	Zr	Zr.v
53	2805	Income to Needs	dichotomized internalizing	-0.16	-0.16	-0.16	0.00036
54	2805		dichotomized internalizing	0.015	0.065	0.065	0.00036
57	1517	continuous income	YSR continuous	NA	-0.07	-0.07	0.00066
58	1517	continuous income	YSR continuous	NA	-0.03	-0.03	0.00066
89	771	dollar income	sum z score of DISC dep, sep anx, overanx, soc phob	NA	-0.21	-0.21	0.0013
93	771	dollar income	sum z score of DISC add, conduct, odd	NA	-0.18	-0.18	0.0013
97	1589	dollar income	Sum of CBCL Ext. items	NA	-0.082	-0.082	0.00063
101	2257	dollar income	Sum of CBCL Ext. items	NA	-0.13	-0.14	0.00044
105	2230	dollar income	Sum of CBCL Int. items	NA	-0.11	-0.11	0.00045
109	823	SES stress' coded 1-3 where 3 represents a low hollingshead index	ACQ Externalizing Scale	0	0	0	0.0012
110	823	SES stress' coded 1-3 where 3 represents a low hollingshead index	ACQ Internalizing Scale	-0.04	-0.039	-0.039	0.0012
111	823	# of forms of Assistance	ACQ Externalizing Scale	0.1	0.15	0.15	0.0012
112	823	# of forms of Assistance	ACQ Internalizing Scale	-0.01	-0.0098	-0.0098	0.0012
113	1455	dollar income	Sum of CDI:S	NA	0.011	0.011	0.00069
117	1045	dollar income	Sum of CDI:S	NA	-0.0041	-0.0041	0.00096

6.4 Data check

Since we are going to do some secondary conversions now, let's make a factor variable to keep track of what parameter was originally entered.

```
esdf$p.entered<-NA
esdf[is.na(esdf$rpb) & is.na(esdf$g) & is.na(esdf$Zr),]$p.entered<-"lOR"
esdf[is.na(esdf$rpb) & is.na(esdf$lOR) & is.na(esdf$Zr),]$p.entered<-"g"
esdf[!is.na(esdf$rpb) & is.na(esdf$lOR) & is.na(esdf$Zr),]$p.entered<-"g2"
esdf[is.na(esdf$rpb) & is.na(esdf$lOR) & is.na(esdf$g),]$p.entered<-"Zr"
```

We should now have 1 and only 1 meta-analysis ready parameter for each study, and a p.entered var for every row.

efid	parameters	entered
1	1	Zr
2	1	Zr
3	1	g
4	1	g
5	1	lOR
6	1	lOR
7	1	lOR
8	1	lOR
9	1	lOR
10	1	lOR
11	1	lOR
12	1	lOR
13	1	lOR
14	1	lOR
15	1	lOR
16	1	g2
17	1	lOR
18	1	lOR
19	1	lOR
20	1	g2
21	1	lOR
22	1	lOR
23	1	lOR
24	1	g2
25	1	lOR
26	1	lOR
27	1	lOR
28	1	g2
29	1	lOR
30	1	lOR
31	1	lOR
32	1	lOR
33	1	lOR
34	1	lOR
35	1	lOR
36	1	lOR
37	1	lOR

efid	parameters	entered
38	1	lOR
39	1	lOR
40	1	lOR
41	1	lOR
42	1	lOR
43	1	lOR
44	1	lOR
45	1	lOR
46	1	lOR
47	1	g
48	1	g
49	1	Zr
50	1	Zr
51	1	Zr
52	1	Zr
53	1	Zr
54	1	Zr
55	1	lOR
56	1	lOR
57	1	Zr
58	1	Zr
59	1	lOR
60	1	lOR
61	1	lOR
62	1	lOR
63	1	lOR
64	1	lOR
65	1	lOR
66	1	lOR
67	1	lOR
68	1	lOR
69	1	lOR
70	1	lOR
71	1	lOR
72	1	lOR
73	1	g2
74	1	lOR

efid	parameters	entered
75	1	lOR
76	1	lOR
77	1	g2
78	1	lOR
79	1	lOR
80	1	lOR
81	1	g2
82	1	lOR
83	1	lOR
84	1	lOR
85	1	g2
86	1	lOR
87	1	lOR
88	1	lOR
89	1	Zr
90	1	g
91	1	g
92	1	g
93	1	Zr
94	1	g
95	1	g
96	1	g
97	1	Zr
98	1	g
99	1	g
100	1	g
101	1	Zr
102	1	g
103	1	g
104	1	g
105	1	Zr
106	1	g
107	1	g
108	1	g
109	1	Zr
110	1	Zr
111	1	Zr

efid	parameters	entered
112	1	Zr
113	1	Zr
114	1	g
115	1	g
116	1	g
117	1	Zr
118	1	g
119	1	g
120	1	g

7 Effect Parameter Conversion

We will sometimes need to convert our effects (lOR, g, r) in to each other to run particular analyses. This is particularly central for the omnibus model, so we should build some convenience functions for readability. These will rely on the particular data structure for this analysis, so they are not particularly portable, but the underlying logic should be easy to follow.

7.1 Formulas

7.1.1 Z to g

Borenstein's (2009) formula refers to Vr, which makes no sense for raw r, so the formula must be referring to z transformed R. Borenstein's formula is on page 48 (formula 7.5 and 7.6) and is as follows:

$$d = \frac{2r}{\sqrt{1-r^2}}$$

$$V_d = \frac{4V_r}{(1-r^2)^3}$$

Although our samples are sufficiently large that the process is unlikely to produce large corrections, it is recommended to use a bias corrected form of d, hedge's g. This is provided by the following set of formulas, also from Borenstein (2009):

$$J = 1 - \frac{3}{4df - 1}$$

$$g = J \times d$$

$$V_g = J^2 \times V_d$$

Here is the function:

```
dtg<-function(n,d,vd){
  df<-n-2 # We are assuming 2 groups by conducting this analysis.
  J=1-3/(4*df-1)
  g=J*d
  g.v=J^2*vd
  c(g,g.v)
}

ztd<-function(rownum) {
  n<-esdf[rownum,"n"]
  r<-esdf[rownum,"Zr"]
  vr<-esdf[rownum,"Zr.v"]
  d<-2*r/sqrt(1-r^2)
  vd<-4*vr/((1-r^2)^3)
  c(d,vd)
}

ztg<-function(rownum) {
  n<-esdf[rownum,"n"]
  d<-ztd(rownum)[1]
  vd<-ztd(rownum)[2]
  dtg(n,d,vd)
}
```

7.1.2 OR to g

Borenstein (2009) gives:

$$d = lOR \times \frac{\sqrt{3}}{\pi}$$

and:

$$V_d = V_{lOR} \times \frac{3}{\pi^2}$$

g can then be calculated as above

```
lORtg<-function(rownum){
 n<-esdf[rownum,"n"]
 lOR<-esdf[rownum,"lOR"]
 lOR.v<-esdf[rownum,"lOR.v"]
 d<-lOR*(sqrt(3)/pi)
```

```
 d.v<-lOR.v*(3/(pi^2))
 dtg(n,d,d.v)
}
```

7.1.3 g to OR

Borenstein (2009) provides this formula:

$$lOR = d\frac{\pi}{\sqrt{3}}$$

$$V_{lOR} = V_d\frac{\pi^2}{3}$$

```
# The algebraic reversal of the formula for d to g can be problematic,
# but is unlikely to cause problems with our large samples.
gtd<-function(n,g,g.v){
  df<-n-2 # We are assuming 2 groups by conducting this analysis.
  J=1-3/(4*df-1)
  d=g/J
  vd=g.v/J^2
  c(d,vd)
}

gtlOR<-function(rownum) {
  n<-esdf[rownum,"n"]
  g<-esdf[rownum,"g"]
  g.v<-esdf[rownum,"g.v"]
  d<-gtd(n,g,g.v)[1]
  d.v<-gtd(n,g,g.v)[2]
  lOR<-d*(pi/sqrt(3))
  lOR.v<-d.v*(pi^2/3)
  c(lOR,lOR.v)
}
```

7.1.4 z to OR

First we convert to d, and then to OR from d as above.

```
ztlOR<-function(rownum) {
  n<-esdf[rownum,"n"]
```

```
  d<-ztd(rownum)[1]
  d.v<-ztd(rownum)[2]
  lOR<-d*(pi/sqrt(3))
  lOR.v<-d.v*(pi^2/3)
  c(lOR,lOR.v)
}
```

7.1.5 g to z

Borenstein (2009) gives:

$$r = \frac{d}{\sqrt{d^2 + a}}$$

$$a = \frac{(n_1 + n_2)^2}{n_1 n_2}$$

$$V_r = \frac{a^2 V_d}{(D^2 + a)^3}$$

```
gtz<-function(rownum) {
  n1<-esdf[rownum,]$n1ib
  n2<-esdf[rownum,]$n2ib
  g<-esdf[rownum,"g"]
  g.v<-esdf[rownum,"g.v"]
  d<-gtd(n1+n2,g,g.v)[1]
  d.v<-gtd(n1+n2,g,g.v)[2]
  a<-(n1+n2^2)/(n1*n2)
  Zr<-d/sqrt(d^2+a)
  Zr.v<-(a^2*d.v)/(d^2+a)^3
  c(Zr,Zr.v)
}
```

7.1.6 OR to z

We convert from OR to d as above. Then Borenstein (2009) gives:

$$r = \frac{d}{\sqrt{d^2 + a}}$$

$$V_r = \frac{a^2 V_d}{(d^2 + a)^3}$$

a is based on n1 and n2, which are not known here, so we can approximate a=4.

```
ORtz<-function(rownum) {
  n<-esdf[rownum,"n"]
  lOR<-esdf[rownum,"lOR"]
  lOR.v<-esdf[rownum,"lOR.v"]
  d<-lOR*(sqrt(3)/pi)
  d.v<-lOR.v*(3/(pi^2))
  r=d/sqrt(d^2+4)
  r.v=(16*d.v)/(d^2+4)^3
  c(r,r.v)
}
```

7.2 Data conversion

Everything will need to be converted to OR and g. One odds ratio will need to be converted to Zr. To minimize the calculations, we will do this by entered parameter.

from g to lOR:

```
trows<-which(esdf$p.entered=="g" | esdf$p.entered=="rpb")
esdf[trows,c("lOR","lOR.v")]<-t(sapply(trows,gtlOR))
```

From lOR to g:

```
trows<-which(esdf$p.entered=="lOR")
esdf[trows,c("g","g.v")]<-t(sapply(trows,lORtg))
```

From zr to g & lOR:

```
trows<-which(esdf$p.entered=="Zr")
esdf[trows,c("g","g.v")]<-t(sapply(trows,ztg))
esdf[trows,c("lOR","lOR.v")]<-t(sapply(trows,ztlOR))
```

From g to z (we'll just do this for the effect that needs it).

```r
trows<-69
esdf[trows,c("Zr","Zr.v")]<-t(sapply(trows,ORtz))
```

8 Reverse Coding

The g scores for family income, subjective SES, and Hollingshead (only for CDP) are often(but not always) reversed from where we want them for a combined analysis, because higher values of the predictor indicate more resources rather than less (as is the case with poverty, parent ed, public assistance). We will code a new variable, gcor, such that a higher g always represents more psychopathology with fewer resources.

```r
esdf$gcor<-esdf$g
rev<-esdf[esdf$IV %in% c("Family Income","Hollingshead","Subjective SES"),"efid"]
rev<-rev[!rev%in%c("31","59","60","62","63","69","109","110")]

esdf[esdf$efid %in% rev,]$gcor<-esdf[esdf$efid %in% rev,]$g*-1
```

	study.ID	IV	sesOper	g	gcor	efid
1	CDP	Hollingshead	Continuous Hollingshead	-0.48	0.48	1
2	CDP	Hollingshead	Continuous Hollingshead	-0.24	0.24	2
16	MECA	Family Income	Continuous $ Income	-0.2	0.2	16
20	MECA	Family Income	Continuous $ Income	-0.17	0.17	20
24	MECA	Family Income	Continuous $ Income	-0.18	0.18	24
28	MECA	Family Income	Continuous $ Income	-0.39	0.39	28
31	NCSA	Family Income	< 3*Poverty Line	0.14	0.14	31
40	NCSA	Subjective SES	Community Ladder	-0.12	0.12	40
41	NCSA	Subjective SES	Community Ladder	-0.12	0.12	41
42	NCSA	Subjective SES	Community Ladder	-0.2	0.2	42
50	PHDCN	Family Income	Income to Needs	-0.094	0.094	50
53	PHDCN	Family Income	Income to Needs	-0.33	0.33	53
57	PHDCN	Family Income	continuous income	-0.14	0.14	57
58	PHDCN	Family Income	continuous income	-0.06	0.06	58
59	PYS	Hollingshead	low SES (Hollingshead=1)	0.29	0.29	59
60	PYS.m	Hollingshead	low SES (Hollingshead=1)	0.26	0.26	60
62	PYS.m	Hollingshead	low SES (Hollingshead=1)	0.38	0.38	62
63	PYS.o	Hollingshead	low SES (Hollingshead=1)	0.22	0.22	63
69	PYS.y	Hollingshead	low SES (Hollingshead=1)	0.26	0.26	69
73	CIC	Family Income	dollar income	-0.4	0.4	73
77	CIC	Family Income	dollar income	-0.56	0.56	77
81	CIC	Family Income	dollar income	-0.38	0.38	81

	study.ID	IV	sesOper	g	gcor	efid
85	CIC	Family Income	dollar income	-0.45	0.45	85
89	CIC	Family Income	dollar income	-0.43	0.43	89
93	CIC	Family Income	dollar income	-0.37	0.37	93
97	FF	Family Income	dollar income	-0.16	0.16	97
101	FF	Family Income	dollar income	-0.27	0.27	101
105	FF	Family Income	dollar income	-0.22	0.22	105
109	NSPC	Hollingshead	SES stress' coded 1-3 where 3 represents a low hollingshead index	0	0	109
110	NSPC	Hollingshead	SES stress' coded 1-3 where 3 represents a low hollingshead index	-0.078	-0.078	110
113	PSID.CDS2	Family Income	dollar income	0.022	-0.022	113
117	PSID.CDS2014	Family Income	dollar income	-0.0082	0.0082	117

(According to their SES operationalization, all of these but 31, 59, 60, 62, 63, 69, 109, 110 should be reversed)

9 Covariance Estimation

Formally, we need to provide a covariance matrix because our effects are not independent. Some of the more common strategies to work around this requirement are not practical in our case: we can't rely on our multilevel model to account for covariance because our samples are not independent, and we don't have enough degrees of freedom to use robust estimation. We also can't get a complete and perfectly accurate covariance matrix:

- We don't have complete correlation data for every study (although we are on better than average ground here).
- For some models we have overlapping 'treatment' categories (i.e., public assistance and poverty are substantially overlapping) and correlated 'outcome' variables. To the best of our knowledge there are no well-established methods for calculating covariance between effect sizes in this circumstance.

Although this is a formal requirement, in practice, the three level model has been shown to deal with dependency of effects well (Van den Noortgate et al., 2013). It also weights effects such that the analysis is not unduly biased towards studies with more effects.

Our approach will be to perform basic modeling with a diagonal covariance structure and then test sensitivity to higher levels of effect covariance within studies. We can use correlations between SES and psychopathology variables to find the highest correlation between component variables in each effect, then use the distribution of these correlations to get a 'high estimate' of correlation between component variables. Conducting a sensitivity test based on the high end of the range will represent a best effort to calculate covariance based on correlations between psychopathology and SES variables. We also present sensitivity tests over a wider range of covariance estimates at the end of this document under 'supplemental analyses.'

9.1 Covariance calculations

var_rho_estimate calculates an estimated correlation between psychopathology variables (or SES variables in cases where the psychopathology variables are the same) within each study and outputs a list of correlation tables.

These correlations can then be provided to formulas provided by Wei & Higgins (2013) (implemented in the 'metavcov' package). The formulas are specific to the g parameter.

```
#This is a matrix of correlations between psychopathology variables based on MECA and GSM
psychcorr<-read.csv("Psych Correlations-meca and copeland.csv",check.names=FALSE,row.names=1)

sescorlist<-readRDS("sescorlist.Rds") #A list of per-study correlation matrices between SES variables
sescorlist[['FF']]<-sescorlist[['ff']]
sescorlist<-lapply(sescorlist,rbind,Hollingshead=0,"Subjective SES"=0) #NAs or Nulls don't appear to work here.
sescorlist<-lapply(sescorlist,cbind,Hollingshead=0,"Subjective SES"=0)
imputed_rhos<-list()
for(name in levels(esdf$study.ID)) {
  if(name %in% names(sescorlist)) {
    imputed_rhos[[name]]<-sescorlist[[name]]
  } else {
    imputed_rhos[[name]]<-sescorlist[["default"]]
  }
}

#This function estimates the highest correlation between non-shared component variables related to each effect in a cohort.

var_rho_estimate<-function(df,use_ses=TRUE) {
  vi_list<-split(df$g.v,df$study.ID,drop=TRUE)
  dv_list<-split(df$DV,df$study.ID,drop=TRUE)
  iv_list<-split(df$IV,df$study.ID,drop=TRUE)
  r_list <-lapply(dv_list,function(X) as.matrix(psychcorr[as.character(X),as.character(X)]))
  r2_list<-lapply(seq_along(iv_list),
                  function(y, n, i) {
                    as.matrix(imputed_rhos[[n[[i]]]][as.character(y[[i]]),as.character(y[[i]])])
                    },
                  y=iv_list, n=names(iv_list)) #i is the sequence here as it is not specified
  r3_list<-lapply(seq_along(r_list),
                  function(y, i) {
                    ifelse(y[[i]]==1,r2_list[[i]],y[[i]])
                  },
```

```
                  y=r_list)
  r4_list<-lapply(r3_list,function(x) {diag(x)<-1; x})
  if(use_ses) {
    return(r4_list)
  } else {
    return(r_list)
  }
}
```

9.2 Estimate of covariance based on FF at year 9.

We will use FF for a ballpark estimate of variable correlations as we have the most data for that study. Here are the effects in question:

	efid	IVshort	DVshort	p.entered
102	102	Poverty	Ext. w2	g
103	103	Parent Ed.	Ext. w2	g
104	104	Assistance	Ext. w2	g
106	106	Poverty	Int. w2	g
107	107	Parent Ed.	Int. w2	g
108	108	Assistance	Int. w2	g

Only two outcomes but 6 effects. We're going to treat each outcome-treatment pair as an 'outcome' and use our above functions to estimate their likely covariance from what we know about the correlation structure of the FF data. We will just look at SMD where we have group counts.

Although the function optionally accepts one, we don't have an estimate of overlapping events (i.e. families with poverty and low parental education). This is ok: the function either uses the r value OR assumes the smaller 'treatment' group is entirely overlapping, which should provide a liberal estimate of covariance, which is what we want for a sensitivity test anyway.

```
ffdf<-esdf[esdf$study.ID=="FF" & esdf$DV!="Externalizing symptoms" & !is.na(esdf$n1ia),]
ffvcov<-metavcov::smd.vcov(nt=t(as.matrix(ffdf$n1ia)),
         nc=t(as.matrix(ffdf$n2ia)),
         d=t(as.matrix(ffdf$g)),
         r=var_rho_estimate(ffdf))$list.smd.cov[[1]]
```

Estimated covariance between effects is now given by ffvcov:

0.002	0.00047	0.00092	0.00056	0.00052	0.00052
0.00047	0.0039	0.00045	0.00052	0.0011	0.0011

0.00092	0.00045	0.0052	0.00052	0.0011	0.0014
0.00056	0.00052	0.00052	0.002	0.00047	0.00092
0.00052	0.0011	0.0011	0.00047	0.0039	0.00045
0.00052	0.0011	0.0014	0.00092	0.00045	0.0052

We can then use cov2cor to print implied correlations between effects:

1	0.17	0.28	0.28	0.19	0.16
0.17	1	0.1	0.19	0.28	0.24
0.28	0.1	1	0.16	0.24	0.28
0.28	0.19	0.16	1	0.17	0.28
0.19	0.28	0.24	0.17	1	0.1
0.16	0.24	0.28	0.28	0.1	1

These should be saved:

```
ffescorr<-cov2cor(ffvcov)
diag(ffescorr)<-NA
```

Considering this set of correlations, mean correlation is 0.2063259, 5th and 95th percentile are 0.1009511, 0.282318.

We'll repeat this with GSM, which we also have relevant data for (albeit with fewer effects), to see if FF is an outlier:

```
gsmdf<-esdf[esdf$study.ID=="GSM" & !is.na(esdf$n1ia),]
gsmvcov<-metavcov::smd.vcov(nt=t(as.matrix(gsmdf$n1ia)),
         nc=t(as.matrix(gsmdf$n2ia)),
         d=t(as.matrix(gsmdf$g)),
         r=var_rho_estimate(gsmdf))$list.smd.cov[[1]]
pander(cov2cor(gsmvcov))
```

1	0.054
0.054	1

GSM shows lower correlations.

Now we make variables based on the distribution from FF:

```
corestlow<-.1010
corestmid<-.2063
coresthigh<-.2823
```

These estimates would be stronger with a formula that accounted simultaneously for overlapping treatments and correlated outcomes, but an average correlation between effect sizes of 0.2063 (CI [0.101-0.2823]) is likely a good broad estimate, although it may be biased somewhat low. We can do sensitivity analyses within this range, which should allow us to get past this issue (since, again, we expect the three level model to take care of this problem in practice). We will also conduct some sensitivity tests with more arbitrary values later.

The following is a wrapper function for clubSandwich::impute_covariance_matrix which we will use to supply covariance matrices to our models.

Going in to the modeling code: clubSandwich::impute_covariance_matrix(vi,“study.ID”,coresthigh) will estimate a covariance matrix based on an imputed correlation between effects of .2823, a value taken from the 95th percentile of our estimated correlations above.

```
get_covariance_matrix<-function (vi, dv, cluster, return_list = identical(as.factor(cluster),
     sort(as.factor(cluster))))
{ clubSandwich::impute_covariance_matrix(vi,cluster,coresthigh)}
```

10 Omnibus Model.

We will try and put everything in to the same model. This approach gives us more power with which to analyze moderation. Some concerns with this approach: we are making some assumptions about the nature of the data by converting everything to g, and (as opposed to a single predictor approach) and correlations between SES measures are an additional source of non-independence. However, in practice the first issue is commonly ignored and the second is handled well by our multivariate approach. We later present bivariate models as a more assumption-free alternative

```
m.combined<-rma.mv(yi=gcor,
                         V=g.v,
                         random=~1 | study.ID/efid,
                         slab=paste(study.ID, efid,sep=" "),
                         data=esdf
                         )

m.combined.corestlow<-rma.mv(yi=gcor,
                         V=clubSandwich::impute_covariance_matrix(esdf$g.v,esdf$study.ID,corestlow),
                         random=~1 | study.ID/efid,
                         slab=paste(study.ID, efid,sep=" "),
                         data=esdf
                         )

m.combined.corestmid<-rma.mv(yi=gcor,
```

```r
                             V=clubSandwich::impute_covariance_matrix(esdf$g.v,esdf$study.ID,corestmid),
                             random=~1 | study.ID/efid,
                             slab=paste(study.ID, efid,sep=" "),
                             data=esdf
                             )

m.combined.coresthigh<-rma.mv(yi=gcor,
                             V=clubSandwich::impute_covariance_matrix(esdf$g.v,esdf$study.ID,coresthigh),
                             random=~1 | study.ID/efid,
                             slab=paste(study.ID, efid,sep=" "),
                             data=esdf
                             )

summary(m.combined)
```

```
##
## Multivariate Meta-Analysis Model (k = 120; method: REML)
##
##   logLik  Deviance       AIC       BIC      AICc
##  42.6230  -85.2460  -79.2460  -70.9087  -79.0373
##
## Variance Components:
##
##             estim    sqrt  nlvls  fixed         factor
## sigma^2.1  0.0158  0.1257     16     no       study.ID
## sigma^2.2  0.0068  0.0826    120     no  study.ID/efid
##
## Test for Heterogeneity:
## Q(df = 119) = 497.1743, p-val < .0001
##
## Model Results:
##
## estimate      se    zval    pval   ci.lb   ci.ub
##   0.2491  0.0352  7.0660  <.0001  0.1800  0.3182  ***
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
confint(m.combined)
```

```
## [[1]]
##
##            estimate  ci.lb  ci.ub
## sigma^2.1    0.0158 0.0069 0.0398
## sigma.1      0.1257 0.0828 0.1994
##
##
## [[2]]
##
##            estimate  ci.lb  ci.ub
## sigma^2.2    0.0068 0.0038 0.0116
## sigma.2      0.0826 0.0619 0.1077
```

```r
comptable<-function(models,labels){
  table<-data.frame(sapply(models,
              function(X) c(X$b,ci.lb=X$ci.lb[[1]],ci.ub=X$ci.ub[[1]],X$sigma2)))
  colnames(table)<-labels
  rownames(table)<-c(dimnames(models[[1]]$b)[[1]],"int.ci.l","int.ci.u","s2between","s2within")
  table$diff<-table[,dim(table)[2]]-table[,1]
  table
}

m.combined.comptable<-comptable(list(m.combined,m.combined.corestlow,m.combined.corestmid,m.combined.coresthigh),
                                c("none","low","mid","high"))
```

The model is very heterogeneous, with a spread in precision past the center line.

	none	low	mid	high	diff
intrcpt	0.25	0.25	0.24	0.24	-0.0052
int.ci.l	0.18	0.18	0.18	0.18	-0.0035
int.ci.u	0.32	0.31	0.31	0.31	-0.0068
s2between	0.016	0.014	0.013	0.013	-0.0029
s2within	0.0068	0.0072	0.0077	0.0081	0.0012

Our covariance estimates introduce relatively little variation. Difference in estimate between highest and none is about .005 (in standard units).

10.1 Bias

We need to test for publication bias in the analysis. The usual way to do this is to perform a test of funnel plot symmetry. There are a number of problems with this approach, namely that it is not necessarily robust to multi-level modeling and is generally not considered appropriate when there is substantial heterogeneity. What's more, several of the usually performed statistical tests can't be run on multilevel meta-analytic models. We will use Egger's regression test by testing the moderating effect of variance (see https://stat.ethz.ch/pipermail/r-sig-meta-analysis/2018-February/000610.html). We can also draw a funnel plot. Finally, a test for moderation by poverty focus is a final, and more elegant, way to test for bias.

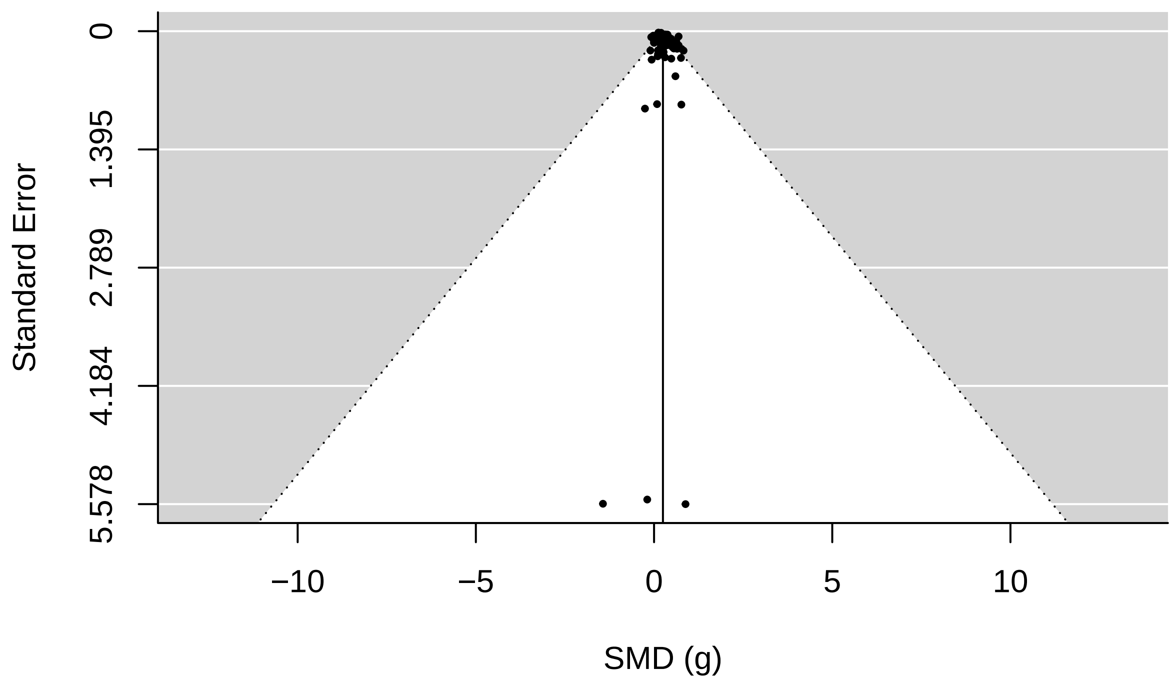
```
m.combined.eggers<-rma.mv(yi=gcor,
                         V=g.v,
                         mods= ~ g.v ,
                         random=~1 | study.ID/efid,
                         slab=paste(study.ID, efid,povFocus,sep=" "),
                         data=esdf
                         )

summary(m.combined.eggers)
```

```
##
## Multivariate Meta-Analysis Model (k = 120; method: REML)
##
##   logLik  Deviance       AIC       BIC      AICc
##  45.2377  -90.4755  -82.4755  -71.3927  -82.1215
##
## Variance Components:
##
##             estim    sqrt  nlvls  fixed         factor
## sigma^2.1  0.0158  0.1258     16     no       study.ID
## sigma^2.2  0.0068  0.0826    120     no  study.ID/efid
##
## Test for Residual Heterogeneity:
## QE(df = 118) = 496.6381, p-val < .0001
##
## Test of Moderators (coefficient(s) 2):
## QM(df = 1) = 0.0185, p-val = 0.8919
##
## Model Results:
##
##          estimate      se     zval    pval    ci.lb   ci.ub
## intrcpt    0.2493  0.0353   7.0622  <.0001   0.1801  0.3184  ***
```

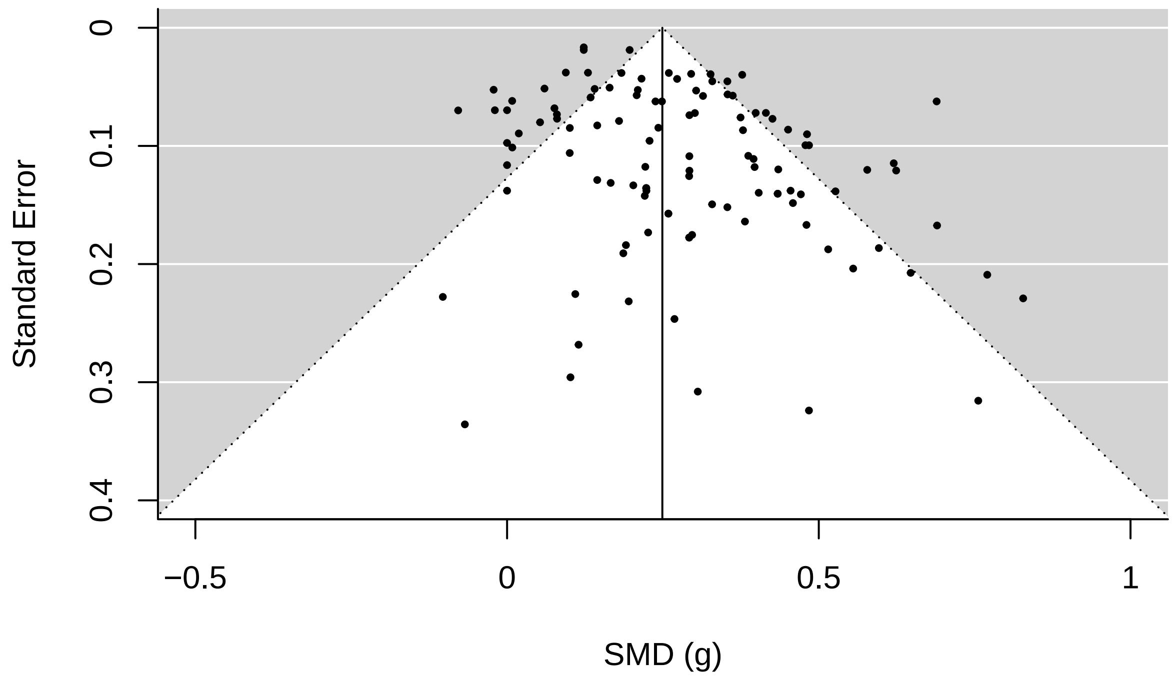
```
## g.v        -0.0139  0.1023  -0.1359  0.8919  -0.2144  0.1866
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

There is little evidence of effect variance on estimates. This indicates that smaller/less accurate studies (which generally are more prone to bias) don't show larger or smaller effects than large ones.

```
funnel(m.combined,pch=19,cex=.4,xlab = "SMD (g)")
```




```
#svg(filename="plot-funnel.svg",height=3.25,width=3.25,pointsize=10,family="sans")
funnel(m.combined,ylim=c(0,.4),xlim=c(-.5,1),pch=19,cex=.4,xlab = "SMD (g)")
```




```
#dev.off()
```

The funnel plot is not obviously asymmetrical. Our moderator test of poverty focus was not significant. The default plot is hard to read, because a few effects from studies without psychopathology had very large variance (these are from studies where little or no psychopathology was reported). Therefore, in the article, a few effects with se above .4 are not displayed.

10.2 Moderation

10.2.1 SES Measure moderation

```r
m.combined.iv<-rma.mv(yi=gcor,
                         V=g.v,
                         mods= ~ IVshort,
                         random=~1 | study.ID/efid,
                         slab=paste(study.ID, efid,IVshort,sep=" "),
                         data=esdf,
                         intercept=TRUE,
                         )

m.combined.iv.corestlow<-rma.mv(yi=gcor,
                         V=clubSandwich::impute_covariance_matrix(esdf$g.v,esdf$study.ID,.21),
                         mods= ~ IVshort,
                         random=~1 | study.ID/efid,
                         slab=paste(study.ID, efid,IVshort,sep=" "),
                         data=esdf
                         )

m.combined.iv.corestmid<-rma.mv(yi=gcor,
                         V=clubSandwich::impute_covariance_matrix(esdf$g.v,esdf$study.ID,corestmid),
                         mods= ~ IVshort,
                         random=~1 | study.ID/efid,
                         slab=paste(study.ID, efid,IVshort,sep=" "),
                         data=esdf
                         )

m.combined.iv.coresthigh<-rma.mv(yi=gcor,
                         V=clubSandwich::impute_covariance_matrix(esdf$g.v,esdf$study.ID,coresthigh),
                         mods= ~ IVshort,
                         random=~1 | study.ID/efid,
                         slab=paste(study.ID, efid,IVshort,sep=" "),
                         data=esdf
                         )

summary(m.combined.iv)
```

```
##
## Multivariate Meta-Analysis Model (k = 120; method: REML)
##
##   logLik  Deviance       AIC       BIC      AICc
```

```
##  43.6446  -87.2892  -71.2892  -49.3996  -69.9178
##
## Variance Components:
##
##             estim    sqrt  nlvls  fixed         factor
## sigma^2.1  0.0170  0.1306     16     no       study.ID
## sigma^2.2  0.0060  0.0777    120     no  study.ID/efid
##
## Test for Residual Heterogeneity:
## QE(df = 114) = 410.5172, p-val < .0001
##
## Test of Moderators (coefficient(s) 2:6):
## QM(df = 5) = 12.8704, p-val = 0.0246
##
## Model Results:
##
##                      estimate      se    zval    pval    ci.lb   ci.ub
## intrcpt                0.1913  0.0453  4.2200  <.0001   0.1024  0.2801  ***
## IVshortHollingshead    0.0212  0.0697  0.3040  0.7611  -0.1154  0.1578
## IVshortParent Ed.      0.0604  0.0372  1.6213  0.1050  -0.0126  0.1333
## IVshortPoverty         0.0595  0.0356  1.6698  0.0950  -0.0103  0.1294    .
## IVshortAssistance      0.1296  0.0383  3.3831  0.0007   0.0545  0.2046  ***
## IVshortSubjective      0.0505  0.0686  0.7365  0.4614  -0.0839  0.1849
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
summary(m.combined.iv.coresthigh)
```

```
##
## Multivariate Meta-Analysis Model (k = 120; method: REML)
##
##   logLik  Deviance       AIC       BIC      AICc
##  45.6953  -91.3906  -75.3906  -53.5010  -74.0191
##
## Variance Components:
##
##             estim    sqrt  nlvls  fixed         factor
## sigma^2.1  0.0152  0.1234     16     no       study.ID
## sigma^2.2  0.0071  0.0843    120     no  study.ID/efid
```

```
##
## Test for Residual Heterogeneity:
## QE(df = 114) = 363.3239, p-val < .0001
##
## Test of Moderators (coefficient(s) 2:6):
## QM(df = 5) = 12.9385, p-val = 0.0240
##
## Model Results:
##
##                       estimate      se    zval    pval    ci.lb   ci.ub
## intrcpt                 0.1948  0.0447  4.3608  <.0001   0.1072  0.2824  ***
## IVshortHollingshead     0.0181  0.0672  0.2689  0.7880  -0.1137  0.1498
## IVshortParent Ed.       0.0526  0.0369  1.4247  0.1542  -0.0198  0.1249
## IVshortPoverty          0.0564  0.0352  1.6032  0.1089  -0.0126  0.1254
## IVshortAssistance       0.1288  0.0383  3.3590  0.0008   0.0536  0.2039  ***
## IVshortSubjective       0.0298  0.0786  0.3791  0.7046  -0.1243  0.1839
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
confint(m.combined.iv)
```

```
## [[1]]
##
##            estimate  ci.lb  ci.ub
## sigma^2.1    0.0170 0.0075 0.0428
## sigma.1      0.1306 0.0864 0.2069
##
##
## [[2]]
##
##            estimate  ci.lb  ci.ub
## sigma^2.2    0.0060 0.0033 0.0105
## sigma.2      0.0777 0.0573 0.1025
```

```r
SESpredict<-as.data.frame(predict(m.combined.iv))
SESpredict$IV<-esdf$IV
uniqueSESpredict<-as.data.frame(SESpredict %>% group_by_all %>% count)
pander(uniqueSESpredict[order(uniqueSESpredict$pred),c(7,8,1:6)])
```

IV	n	pred	se	ci.lb	ci.ub	cr.lb	cr.ub
Family Income	20	0.19	0.045	0.1	0.28	-0.12	0.5
Hollingshead	9	0.21	0.064	0.087	0.34	-0.11	0.54
Subjective SES	3	0.24	0.072	0.1	0.38	-0.088	0.57
Poverty Status (poverty line)	31	0.25	0.043	0.17	0.34	-0.059	0.56
Parental Ed	31	0.25	0.046	0.16	0.34	-0.059	0.56
Receipt of Public Assistance	26	0.32	0.044	0.23	0.41	0.011	0.63

```
m.combined.iv.comptable<-comptable(list(m.combined.iv,m.combined.iv.corestlow,m.combined.iv.corestmid,m.combined.iv.coresthigh),
                                   c("none","low","mid","high"))
pander(m.combined.iv.comptable)
```

	none	low	mid	high	diff
intrcpt	0.19	0.19	0.19	0.19	0.0035
IVshortHollingshead	0.021	0.019	0.019	0.018	-0.0031
IVshortParent Ed.	0.06	0.054	0.055	0.053	-0.0078
IVshortPoverty	0.06	0.057	0.057	0.056	-0.0031
IVshortAssistance	0.13	0.13	0.13	0.13	-0.00076
IVshortSubjective	0.051	0.034	0.035	0.03	-0.021
int.ci.l	0.1	0.11	0.11	0.11	0.0048
int.ci.u	0.28	0.28	0.28	0.28	0.0022
s2between	0.017	0.016	0.016	0.015	-0.0018
s2within	0.006	0.0068	0.0068	0.0071	0.0011

Covariance estimation doesn't seem to create large differences in estimates (the maximum difference in estimate is 0.0048073, although it should be noted that these differences are not necessarily small proportionally to the (non significant) moderator coefficients.

Receipt of public assistance tends to have a particularly strong effect.

10.2.2 Ext/Int moderation

```
m.combined.intext<-rma.mv(yi=gcor,
                          V=g.v,
                          mods= ~ Externalizing,
                          random=~1 | study.ID/efid,
                          slab=paste(study.ID, efid,Externalizing,sep=" "),
```

```r
                         data=esdf
                         )

m.combined.intext.coresthigh<-rma.mv(yi=gcor,
                         V=clubSandwich::impute_covariance_matrix(esdf$g.v,esdf$study.ID,coresthigh),
                         mods= ~ Externalizing,
                         random=~1 | study.ID/efid,
                         slab=paste(study.ID, efid,Externalizing,sep=" "),
                         data=esdf
                         )

summary(m.combined.intext)
```

```
##
## Multivariate Meta-Analysis Model (k = 120; method: REML)
##
##   logLik  Deviance       AIC       BIC      AICc
##  43.9027  -87.8053  -79.8053  -68.7226  -79.4513
##
## Variance Components:
##
##             estim    sqrt  nlvls  fixed         factor
## sigma^2.1  0.0137  0.1169     16     no       study.ID
## sigma^2.2  0.0066  0.0814    120     no  study.ID/efid
##
## Test for Residual Heterogeneity:
## QE(df = 118) = 444.5743, p-val < .0001
##
## Test of Moderators (coefficient(s) 2):
## QM(df = 1) = 4.7097, p-val = 0.0300
##
## Model Results:
##
##                    estimate      se    zval    pval   ci.lb   ci.ub
## intrcpt              0.2216  0.0355  6.2504  <.0001  0.1521  0.2911  ***
## ExternalizingTRUE    0.0576  0.0265  2.1702  0.0300  0.0056  0.1096    *
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
summary(m.combined.intext.coresthigh)
```

```
##
## Multivariate Meta-Analysis Model (k = 120; method: REML)
##
##   logLik  Deviance       AIC       BIC      AICc
##  46.2105  -92.4210  -84.4210  -73.3382  -84.0670
##
## Variance Components:
##
##             estim    sqrt  nlvls  fixed         factor
## sigma^2.1  0.0105  0.1026     16     no       study.ID
## sigma^2.2  0.0078  0.0883    120     no  study.ID/efid
##
## Test for Residual Heterogeneity:
## QE(df = 118) = 390.0033, p-val < .0001
##
## Test of Moderators (coefficient(s) 2):
## QM(df = 1) = 5.4029, p-val = 0.0201
##
## Model Results:
##
##                     estimate      se    zval    pval   ci.lb   ci.ub
## intrcpt               0.2153  0.0341  6.3199  <.0001  0.1485  0.2821  ***
## ExternalizingTRUE     0.0601  0.0259  2.3244  0.0201  0.0094  0.1108    *
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
confint(m.combined.intext)
```

```
## [[1]]
##
##           estimate  ci.lb  ci.ub
## sigma^2.1   0.0137 0.0057 0.0351
## sigma.1     0.1169 0.0756 0.1873
##
##
## [[2]]
```

```
##
##           estimate  ci.lb  ci.ub
## sigma^2.2   0.0066 0.0037 0.0113
## sigma.2     0.0814 0.0608 0.1062
```

```
predict(m.combined.intext.coresthigh)[c(1,2),]
```

```
##               pred     se  ci.lb  ci.ub   cr.lb  cr.ub
## CDP 1 TRUE  0.2754 0.0349 0.2071 0.3437  0.0015 0.5493
## CDP 2 FALSE 0.2153 0.0341 0.1485 0.2821 -0.0582 0.4889
```

We see a small moderation such that externalizing effects are stronger.

10.2.3 Age moderation

```
m.combined.age<-rma.mv(yi=gcor,
                         V=g.v,
                         mods= ~ ageMean.c ,
                         random=~1 | study.ID/efid,
                         slab=paste(study.ID, efid,ageMean,sep=" "),
                         data=esdf
                         )

m.combined.age.coresthigh<-rma.mv(yi=gcor,
                         V=clubSandwich::impute_covariance_matrix(esdf$g.v,esdf$study.ID,coresthigh),
                         mods= ~ ageMean.c ,
                         random=~1 | study.ID/efid,
                         slab=paste(study.ID, efid,ageMean,sep=" "),
                         data=esdf
                         )

summary(m.combined.age)
```

```
##
## Multivariate Meta-Analysis Model (k = 120; method: REML)
##
##   logLik  Deviance       AIC       BIC      AICc
##  42.1350  -84.2700  -76.2700  -65.1872  -75.9160
##
## Variance Components:
```

```
##
##              estim    sqrt  nlvls  fixed         factor
## sigma^2.1  0.0160  0.1265     16     no       study.ID
## sigma^2.2  0.0069  0.0834    120     no  study.ID/efid
##
## Test for Residual Heterogeneity:
## QE(df = 118) = 466.4031, p-val < .0001
##
## Test of Moderators (coefficient(s) 2):
## QM(df = 1) = 0.1352, p-val = 0.7131
##
## Model Results:
##
##            estimate      se     zval    pval    ci.lb   ci.ub
## intrcpt      0.2476  0.0357   6.9317  <.0001   0.1776  0.3176  ***
## ageMean.c   -0.0024  0.0066  -0.3677  0.7131  -0.0153  0.0105
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
summary(m.combined.age.coresthigh)
```

```
##
## Multivariate Meta-Analysis Model (k = 120; method: REML)
##
##   logLik  Deviance       AIC       BIC      AICc
##  44.1912  -88.3824  -80.3824  -69.2996  -80.0284
##
## Variance Components:
##
##              estim    sqrt  nlvls  fixed         factor
## sigma^2.1  0.0130  0.1141     16     no       study.ID
## sigma^2.2  0.0082  0.0905    120     no  study.ID/efid
##
## Test for Residual Heterogeneity:
## QE(df = 118) = 401.8885, p-val < .0001
##
## Test of Moderators (coefficient(s) 2):
## QM(df = 1) = 0.2049, p-val = 0.6508
##
```

```
## Model Results:
##
##             estimate      se     zval    pval    ci.lb   ci.ub
## intrcpt       0.2419  0.0348   6.9536  <.0001   0.1737  0.3101  ***
## ageMean.c    -0.0030  0.0066  -0.4527  0.6508  -0.0159  0.0099
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Not significant (NS).

10.2.4 Gender Moderation

```
m.combined.sex<-rma.mv(yi=gcor,
                         V=g.v,
                         mods= ~ femalePerc ,
                         random=~1 | study.ID/efid,
                         slab=paste(study.ID, efid,femalePerc,sep=" "),
                         data=esdf
                         )

m.combined.sex.coresthigh<-rma.mv(yi=gcor,
                         V=clubSandwich::impute_covariance_matrix(esdf$g.v,esdf$study.ID,coresthigh),
                         mods= ~ femalePerc ,
                         random=~1 | study.ID/efid,
                         slab=paste(study.ID, efid,femalePerc,sep=" "),
                         data=esdf
                         )

summary(m.combined.sex)
```

```
##
## Multivariate Meta-Analysis Model (k = 120; method: REML)
##
##   logLik  Deviance       AIC       BIC      AICc
##  42.3584  -84.7167  -76.7167  -65.6340  -76.3627
##
## Variance Components:
##
```

```
##              estim    sqrt  nlvls  fixed        factor
## sigma^2.1  0.0170  0.1304     16     no      study.ID
## sigma^2.2  0.0068  0.0826    120     no  study.ID/efid
##
## Test for Residual Heterogeneity:
## QE(df = 118) = 495.2552, p-val < .0001
##
## Test of Moderators (coefficient(s) 2):
## QM(df = 1) = 0.1397, p-val = 0.7086
##
## Model Results:
##
##              estimate      se     zval    pval    ci.lb   ci.ub
## intrcpt        0.2725  0.0719   3.7886  0.0002   0.1315  0.4134  ***
## femalePerc    -0.0549  0.1468  -0.3737  0.7086  -0.3425  0.2328
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
summary(m.combined.sex.coresthigh)
```

```
##
## Multivariate Meta-Analysis Model (k = 120; method: REML)
##
##   logLik  Deviance       AIC       BIC      AICc
##  44.3569  -88.7139  -80.7139  -69.6311  -80.3599
##
## Variance Components:
##
##              estim    sqrt  nlvls  fixed        factor
## sigma^2.1  0.0141  0.1189     16     no      study.ID
## sigma^2.2  0.0081  0.0898    120     no  study.ID/efid
##
## Test for Residual Heterogeneity:
## QE(df = 118) = 422.0661, p-val < .0001
##
## Test of Moderators (coefficient(s) 2):
## QM(df = 1) = 0.0993, p-val = 0.7526
##
## Model Results:
```

```
##
##              estimate      se     zval    pval    ci.lb   ci.ub
## intrcpt        0.2643  0.0729   3.6248  0.0003   0.1214  0.4073  ***
## femalePerc    -0.0462  0.1467  -0.3152  0.7526  -0.3337  0.2413
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

NS

10.2.5 % Racial Majority / White

```
m.combined.race<-rma.mv(yi=gcor,
                         V=g.v,
                         mods= ~ whitePerc.c ,
                         random=~1 | study.ID/efid,
                         slab=paste(study.ID, efid,whitePerc,sep=" "),
                         data=esdf
                         )

m.combined.race.coresthigh<-rma.mv(yi=gcor,
                         V=clubSandwich::impute_covariance_matrix(esdf$g.v,esdf$study.ID,coresthigh),
                         mods= ~ whitePerc.c ,
                         random=~1 | study.ID/efid,
                         slab=paste(study.ID, efid,whitePerc,sep=" "),
                         data=esdf
                         )

summary(m.combined.race)
```

```
##
## Multivariate Meta-Analysis Model (k = 120; method: REML)
##
##   logLik  Deviance       AIC       BIC      AICc
##  42.7129  -85.4258  -77.4258  -66.3430  -77.0718
##
## Variance Components:
##
##             estim    sqrt  nlvls  fixed        factor
```

```
## sigma^2.1  0.0171  0.1309     16     no       study.ID
## sigma^2.2  0.0068  0.0826    120     no  study.ID/efid
##
## Test for Residual Heterogeneity:
## QE(df = 118) = 495.4283, p-val < .0001
##
## Test of Moderators (coefficient(s) 2):
## QM(df = 1) = 0.0871, p-val = 0.7679
##
## Model Results:
##
##              estimate      se    zval    pval    ci.lb   ci.ub
## intrcpt        0.2462  0.0379  6.5031  <.0001   0.1720  0.3204  ***
## whitePerc.c    0.0511  0.1731  0.2951  0.7679  -0.2882  0.3904
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
summary(m.combined.race.coresthigh)
```

```
##
## Multivariate Meta-Analysis Model (k = 120; method: REML)
##
##   logLik  Deviance       AIC       BIC      AICc
##  44.6657  -89.3313  -81.3313  -70.2486  -80.9773
##
## Variance Components:
##
##             estim    sqrt  nlvls  fixed         factor
## sigma^2.1  0.0143  0.1198     16     no       study.ID
## sigma^2.2  0.0081  0.0898    120     no  study.ID/efid
##
## Test for Residual Heterogeneity:
## QE(df = 118) = 416.4074, p-val < .0001
##
## Test of Moderators (coefficient(s) 2):
## QM(df = 1) = 0.0164, p-val = 0.8980
##
## Model Results:
##
```

```
##                estimate      se    zval    pval    ci.lb   ci.ub
## intrcpt         0.2431  0.0370  6.5659  <.0001   0.1705  0.3156  ***
## whitePerc.c     0.0216  0.1682  0.1282  0.8980  -0.3080  0.3511
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

NS

10.2.6 % African American / Black

```
m.combined.race2<-rma.mv(yi=gcor,
                         V=g.v,
                         mods= ~ blackPerc.c ,
                         random=~1 | study.ID/efid,
                         slab=paste(study.ID, efid,blackPerc,sep=" "),
                         data=esdf
                         )

m.combined.race2.coresthigh<-rma.mv(yi=gcor,
                         V=clubSandwich::impute_covariance_matrix(esdf$g.v,esdf$study.ID,coresthigh),
                         mods= ~ blackPerc.c ,
                         random=~1 | study.ID/efid,
                         slab=paste(study.ID, efid,blackPerc,sep=" "),
                         data=esdf
                         )

summary(m.combined.race2)
```

```
##
## Multivariate Meta-Analysis Model (k = 120; method: REML)
##
##   logLik  Deviance       AIC       BIC      AICc
##  42.7129  -85.4258  -77.4258  -66.3430  -77.0718
##
## Variance Components:
##
##              estim    sqrt  nlvls  fixed        factor
## sigma^2.1  0.0171  0.1309     16     no      study.ID
```

```
## sigma^2.2  0.0068  0.0826    120     no  study.ID/efid
##
## Test for Residual Heterogeneity:
## QE(df = 118) = 495.4283, p-val < .0001
##
## Test of Moderators (coefficient(s) 2):
## QM(df = 1) = 0.0871, p-val = 0.7679
##
## Model Results:
##
##              estimate      se    zval    pval    ci.lb   ci.ub
## intrcpt        0.2462  0.0379  6.5031  <.0001   0.1720  0.3204  ***
## blackPerc.c    0.0511  0.1731  0.2951  0.7679  -0.2882  0.3904
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
summary(m.combined.race2.coresthigh)
```

```
##
## Multivariate Meta-Analysis Model (k = 120; method: REML)
##
##   logLik  Deviance       AIC       BIC      AICc
##  44.6657  -89.3313  -81.3313  -70.2486  -80.9773
##
## Variance Components:
##
##             estim    sqrt  nlvls  fixed         factor
## sigma^2.1  0.0143  0.1198     16     no       study.ID
## sigma^2.2  0.0081  0.0898    120     no  study.ID/efid
##
## Test for Residual Heterogeneity:
## QE(df = 118) = 416.4074, p-val < .0001
##
## Test of Moderators (coefficient(s) 2):
## QM(df = 1) = 0.0164, p-val = 0.8980
##
## Model Results:
##
##              estimate      se    zval    pval    ci.lb   ci.ub
```

```
## intrcpt        0.2431  0.0370  6.5659  <.0001   0.1705  0.3156  ***
## blackPerc.c    0.0216  0.1682  0.1282  0.8980  -0.3080  0.3511
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

NS

10.2.7 Adjustment Moderation

```
m.combined.adj<-rma.mv(yi=gcor,
                         V=g.v,
                         mods= ~ adjusted ,
                         random=~1 | study.ID/efid,
                         slab=paste(study.ID, efid,"adj",adjusted,sep=" "),
                         data=esdf
                         )

m.combined.adj.coresthigh<-rma.mv(yi=gcor,
                         V=clubSandwich::impute_covariance_matrix(esdf$g.v,esdf$study.ID,coresthigh),
                         mods= ~ adjusted ,
                         random=~1 | study.ID/efid,
                         slab=paste(study.ID, efid,"adj",adjusted,sep=" "),
                         data=esdf
                         )

summary(m.combined.adj)
```

```
##
## Multivariate Meta-Analysis Model (k = 120; method: REML)
##
##   logLik  Deviance       AIC       BIC      AICc
##  42.0742  -84.1484  -76.1484  -65.0657  -75.7944
##
## Variance Components:
##
##             estim    sqrt  nlvls  fixed         factor
## sigma^2.1  0.0173  0.1317     16     no       study.ID
## sigma^2.2  0.0067  0.0818    120     no  study.ID/efid
```

```
##
## Test for Residual Heterogeneity:
## QE(df = 118) = 497.1445, p-val < .0001
##
## Test of Moderators (coefficient(s) 2):
## QM(df = 1) = 0.4577, p-val = 0.4987
##
## Model Results:
##
##               estimate      se    zval    pval    ci.lb   ci.ub
## intrcpt         0.2433  0.0376  6.4637  <.0001   0.1695  0.3171  ***
## adjustedTRUE    0.0341  0.0504  0.6765  0.4987  -0.0647  0.1329
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
summary(m.combined.adj.coresthigh)
```

```
##
## Multivariate Meta-Analysis Model (k = 120; method: REML)
##
##   logLik  Deviance       AIC       BIC      AICc
##  44.0907  -88.1813  -80.1813  -69.0986  -79.8273
##
## Variance Components:
##
##              estim    sqrt  nlvls  fixed         factor
## sigma^2.1  0.0145  0.1204     16     no       study.ID
## sigma^2.2  0.0079  0.0890    120     no  study.ID/efid
##
## Test for Residual Heterogeneity:
## QE(df = 118) = 416.6634, p-val < .0001
##
## Test of Moderators (coefficient(s) 2):
## QM(df = 1) = 0.4583, p-val = 0.4984
##
## Model Results:
##
##               estimate      se    zval    pval    ci.lb   ci.ub
## intrcpt         0.2382  0.0369  6.4507  <.0001   0.1658  0.3105  ***
```

```
## adjustedTRUE    0.0340  0.0503  0.6770  0.4984  -0.0645  0.1326
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

NS

10.2.8 Weighting Moderation

```
m.combined.weight<-rma.mv(yi=gcor,
                         V=g.v,
                         mods= ~ weighted ,
                         random=~1 | study.ID/efid,
                         slab=paste(study.ID, efid,"weight",weighted,sep=" "),
                         data=esdf
                         )

m.combined.weight.coresthigh<-rma.mv(yi=gcor,
                         V=clubSandwich::impute_covariance_matrix(esdf$g.v,esdf$study.ID,coresthigh),
                         mods= ~ weighted ,
                         random=~1 | study.ID/efid,
                         slab=paste(study.ID, efid,"weight",weighted,sep=" "),
                         data=esdf
                         )

summary(m.combined.weight)
```

```
##
## Multivariate Meta-Analysis Model (k = 120; method: REML)
##
##   logLik  Deviance       AIC       BIC      AICc
##  43.3151  -86.6302  -78.6302  -67.5475  -78.2763
##
## Variance Components:
##
##               estim    sqrt  nlvls  fixed         factor
## sigma^2.1    0.0150  0.1223     16     no       study.ID
## sigma^2.2    0.0068  0.0827    120     no  study.ID/efid
##
```

```
## Test for Residual Heterogeneity:
## QE(df = 118) = 430.0566, p-val < .0001
##
## Test of Moderators (coefficient(s) 2):
## QM(df = 1) = 1.4181, p-val = 0.2337
##
## Model Results:
##
##               estimate      se     zval    pval    ci.lb   ci.ub
## intrcpt         0.3077  0.0602   5.1131  <.0001   0.1897  0.4256  ***
## weightedTRUE   -0.0874  0.0734  -1.1909  0.2337  -0.2313  0.0565
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
summary(m.combined.weight.coresthigh)
```

```
##
## Multivariate Meta-Analysis Model (k = 120; method: REML)
##
##   logLik  Deviance       AIC       BIC      AICc
##  45.2030  -90.4061  -82.4061  -71.3233  -82.0521
##
## Variance Components:
##
##             estim    sqrt  nlvls  fixed         factor
## sigma^2.1  0.0124  0.1116     16     no       study.ID
## sigma^2.2  0.0081  0.0900    120     no  study.ID/efid
##
## Test for Residual Heterogeneity:
## QE(df = 118) = 401.6178, p-val < .0001
##
## Test of Moderators (coefficient(s) 2):
## QM(df = 1) = 1.1704, p-val = 0.2793
##
## Model Results:
##
##               estimate      se     zval    pval    ci.lb   ci.ub
## intrcpt         0.2967  0.0595   4.9825  <.0001   0.1800  0.4134  ***
## weightedTRUE   -0.0784  0.0724  -1.0818  0.2793  -0.2204  0.0636
```

```
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

10.2.9 Reporter Moderation

```
m.combined.rep<-rma.mv(yi=gcor,
                         V=g.v,
                         mods= ~ measure ,
                         random=~1 | study.ID/efid,
                         slab=paste(study.ID, efid,"measure",measure,sep=" "),
                         data=esdf
                         )

m.combined.rep.coresthigh<-rma.mv(yi=gcor,
                         V=clubSandwich::impute_covariance_matrix(esdf$g.v,esdf$study.ID,coresthigh),
                         mods= ~ measure ,
                         random=~1 | study.ID/efid,
                         slab=paste(study.ID, efid,"measure",measure,sep=" "),
                         data=esdf
                         )

summary(m.combined.rep)
```

```
##
## Multivariate Meta-Analysis Model (k = 120; method: REML)
##
##   logLik  Deviance       AIC       BIC      AICc
##  44.4122  -88.8245  -72.8245  -50.9349  -71.4531
##
## Variance Components:
##
##             estim    sqrt  nlvls  fixed         factor
## sigma^2.1  0.0146  0.1206     16     no       study.ID
## sigma^2.2  0.0062  0.0788    120     no  study.ID/efid
##
## Test for Residual Heterogeneity:
## QE(df = 114) = 422.8100, p-val < .0001
##
```

```
## Test of Moderators (coefficient(s) 2:6):
## QM(df = 5) = 9.3778, p-val = 0.0949
##
## Model Results:
##
##                          estimate      se     zval    pval    ci.lb   ci.ub
## intrcpt                    0.3747  0.1792   2.0915  0.0365   0.0236  0.7259  *
## measureChild Form         -0.2801  0.1890  -1.4821  0.1383  -0.6505  0.0903
## measureCombined           -0.0706  0.1825  -0.3868  0.6989  -0.4283  0.2871
## measureParent Form        -0.1433  0.1857  -0.7720  0.4401  -0.5072  0.2206
## measureParent Interview   -0.0678  0.1801  -0.3765  0.7065  -0.4208  0.2852
## measureTeacher Form       -0.0169  0.2314  -0.0732  0.9416  -0.4706  0.4367
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
summary(m.combined.rep.coresthigh)
```

```
##
## Multivariate Meta-Analysis Model (k = 120; method: REML)
##
##   logLik  Deviance       AIC       BIC      AICc
##  46.4252  -92.8504  -76.8504  -54.9608  -75.4790
##
## Variance Components:
##
##              estim    sqrt  nlvls  fixed         factor
## sigma^2.1   0.0121  0.1100     16     no       study.ID
## sigma^2.2   0.0074  0.0861    120     no  study.ID/efid
##
## Test for Residual Heterogeneity:
## QE(df = 114) = 363.3461, p-val < .0001
##
## Test of Moderators (coefficient(s) 2:6):
## QM(df = 5) = 9.4632, p-val = 0.0920
##
## Model Results:
##
##                          estimate      se     zval    pval    ci.lb   ci.ub
## intrcpt                    0.3937  0.1720   2.2892  0.0221   0.0566  0.7307  *
```

```
## measureChild Form         -0.3016  0.1819  -1.6585  0.0972  -0.6581  0.0548  .
## measureCombined           -0.0939  0.1737  -0.5408  0.5886  -0.4343  0.2465
## measureParent Form        -0.1646  0.1781  -0.9242  0.3554  -0.5135  0.1844
## measureParent Interview   -0.0899  0.1735  -0.5180  0.6045  -0.4299  0.2502
## measureTeacher Form       -0.0362  0.2242  -0.1614  0.8718  -0.4756  0.4032
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

NS

10.2.10 Poverty Focus

```
m.combined.pfoc<-rma.mv(yi=gcor,
                         V=g.v,
                         mods= ~ povFocus ,
                         random=~1 | study.ID/efid,
                         slab=paste(study.ID, efid,povFocus,sep=" "),
                         data=esdf
                         )

m.combined.pfoc.coresthigh<-rma.mv(yi=gcor,
                         V=clubSandwich::impute_covariance_matrix(esdf$g.v,esdf$study.ID,coresthigh),
                         mods= ~ povFocus ,
                         random=~1 | study.ID/efid,
                         slab=paste(study.ID, efid,povFocus,sep=" "),
                         data=esdf
                         )

summary(m.combined.pfoc)
```

```
##
## Multivariate Meta-Analysis Model (k = 120; method: REML)
##
##   logLik  Deviance       AIC       BIC      AICc
##  43.2449  -86.4899  -78.4899  -67.4071  -78.1359
##
## Variance Components:
##
```

```
##              estim    sqrt  nlvls  fixed        factor
## sigma^2.1  0.0186  0.1365     16     no      study.ID
## sigma^2.2  0.0062  0.0789    120     no  study.ID/efid
##
## Test for Residual Heterogeneity:
## QE(df = 118) = 463.8916, p-val < .0001
##
## Test of Moderators (coefficient(s) 2):
## QM(df = 1) = 2.7549, p-val = 0.0970
##
## Model Results:
##
##                estimate      se    zval    pval    ci.lb   ci.ub
## intrcpt          0.2383  0.0382  6.2369  <.0001   0.1634  0.3131  ***
## povFocusTRUE     0.0896  0.0540  1.6598  0.0970  -0.0162  0.1953    .
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
summary(m.combined.pfoc.coresthigh)
```

```
##
## Multivariate Meta-Analysis Model (k = 120; method: REML)
##
##   logLik  Deviance       AIC       BIC      AICc
##  45.1051  -90.2101  -82.2101  -71.1274  -81.8561
##
## Variance Components:
##
##              estim    sqrt  nlvls  fixed        factor
## sigma^2.1  0.0158  0.1259     16     no      study.ID
## sigma^2.2  0.0075  0.0866    120     no  study.ID/efid
##
## Test for Residual Heterogeneity:
## QE(df = 118) = 420.6052, p-val < .0001
##
## Test of Moderators (coefficient(s) 2):
## QM(df = 1) = 2.4471, p-val = 0.1177
##
## Model Results:
```

```
##
##                estimate      se    zval    pval    ci.lb   ci.ub
## intrcpt          0.2330  0.0376  6.1920  <.0001   0.1592  0.3067  ***
## povFocusTRUE     0.0838  0.0535  1.5643  0.1177  -0.0212  0.1887
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

NS

10.2.11 Study Date

```
m.combined.date<-rma.mv(yi=gcor,
                        V=g.v,
                        mods= ~ date.c ,
                        random=~1 | study.ID/efid,
                        slab=paste(study.ID, efid,povFocus,sep=" "),
                        data=esdf
                        )

m.combined.date.coresthigh<-rma.mv(yi=gcor,
                        V=clubSandwich::impute_covariance_matrix(esdf$g.v,esdf$study.ID,coresthigh),
                        mods= ~ date.c ,
                        random=~1 | study.ID/efid,
                        slab=paste(study.ID, efid,povFocus,sep=" "),
                        data=esdf
                        )

summary(m.combined.date)
```

```
##
## Multivariate Meta-Analysis Model (k = 120; method: REML)
##
##   logLik  Deviance       AIC       BIC      AICc
##  43.8336  -87.6673  -79.6673  -68.5846  -79.3133
##
## Variance Components:
##
##             estim    sqrt  nlvls  fixed        factor
```

```
## sigma^2.1  0.0122  0.1105     16     no       study.ID
## sigma^2.2  0.0071  0.0842    120     no  study.ID/efid
##
## Test for Residual Heterogeneity:
## QE(df = 118) = 441.9684, p-val < .0001
##
## Test of Moderators (coefficient(s) 2):
## QM(df = 1) = 3.1208, p-val = 0.0773
##
## Model Results:
##
##          estimate      se     zval    pval    ci.lb   ci.ub
## intrcpt    0.2575  0.0322   7.9847  <.0001   0.1943  0.3207  ***
## date.c    -0.0062  0.0035  -1.7666  0.0773  -0.0132  0.0007    .
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
summary(m.combined.pfoc.coresthigh)
```

```
##
## Multivariate Meta-Analysis Model (k = 120; method: REML)
##
##   logLik  Deviance       AIC       BIC      AICc
##  45.1051  -90.2101  -82.2101  -71.1274  -81.8561
##
## Variance Components:
##
##             estim    sqrt  nlvls  fixed         factor
## sigma^2.1  0.0158  0.1259     16     no       study.ID
## sigma^2.2  0.0075  0.0866    120     no  study.ID/efid
##
## Test for Residual Heterogeneity:
## QE(df = 118) = 420.6052, p-val < .0001
##
## Test of Moderators (coefficient(s) 2):
## QM(df = 1) = 2.4471, p-val = 0.1177
##
## Model Results:
##
```

```
##                  estimate      se    zval    pval    ci.lb   ci.ub
## intrcpt           0.2330  0.0376  6.1920  <.0001   0.1592  0.3067  ***
## povFocusTRUE      0.0838  0.0535  1.5643  0.1177  -0.0212  0.1887
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

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10.3 Further Model Building

Does adding the moderators actually improve model fit? This addresses overfitting. We will need to specify a model with ML, as REML (although less biased) does not allow for these comparisons.

```
m.ml.combined<-rma.mv(yi=gcor,
                         V=g.v,
                         method="ML",
                         random=~1 | study.ID/efid,
                         slab=paste(study.ID, efid,IVshort,sep=" "),
                         data=esdf,
                         intercept=TRUE
                         )

m.ml.combined.iv<-rma.mv(yi=gcor,
                         V=g.v,
                         mods= ~ IVshort,
                         method="ML",
                         random=~1 | study.ID/efid,
                         slab=paste(study.ID, efid,IVshort,sep=" "),
                         data=esdf,
                         intercept=TRUE
                         )

m.ml.combined.intext<-rma.mv(yi=gcor,
                         V=g.v,
                         mods= ~ Externalizing,
                         method="ML",
                         random=~1 | study.ID/efid,
                         slab=paste(study.ID, efid,IVshort,sep=" "),
                         data=esdf,
```

```
                         intercept=TRUE
                         )


m.ml.combined.intext.IV<-rma.mv(yi=gcor,
                         V=g.v,
                         mods= ~ IVshort+Externalizing,
                         method="ML",
                         random=~1 | study.ID/efid,
                         slab=paste(study.ID, efid,Externalizing,sep=" "),
                         data=esdf
                         )

m.ml.combined.intext.IVint<-rma.mv(yi=gcor,
                         V=g.v,
                         mods= ~ IVshort*Externalizing,
                         method="ML",
                         random=~1 | study.ID/efid,
                         slab=paste(study.ID, efid,Externalizing,sep=" "),
                         data=esdf
                         )

m.ml.combined.intext.IVint<-rma.mv(yi=gcor,
                                   V=g.v,
                                   mods= ~ IVshort*Externalizing,
                                   method="ML",
                                   random=~1 | study.ID/efid,
                                   slab=paste(study.ID, efid,Externalizing,sep=" "),
                                   data=esdf
)


anova(m.ml.combined,m.ml.combined.intext.IV)
```

```
##          df      AIC      BIC     AICc  logLik     LRT   pval       QE
## Full      9 -85.0101 -59.9227 -83.3738 51.5051                367.6400
## Reduced   3 -79.3427 -70.9803 -79.1358 42.6714 17.6674 0.0071 497.1743
```

```r
anova(m.ml.combined,m.ml.combined.intext.IVint)
```

```
##         df      AIC      BIC     AICc  logLik     LRT   pval       QE
## Full    14 -86.8365 -47.8116 -82.8365 57.4182                334.7176
## Reduced  3 -79.3427 -70.9803 -79.1358 42.6714 29.4937 0.0019 497.1743
```

```r
anova(m.ml.combined.intext.IVint,m.ml.combined.intext.IV)
```

```
##         df      AIC      BIC     AICc  logLik     LRT   pval       QE
## Full    14 -86.8365 -47.8116 -82.8365 57.4182                334.7176
## Reduced  9 -85.0101 -59.9227 -83.3738 51.5051 11.8263 0.0372 367.6400
```

```r
intcellcounts<-gmodels::CrossTable(esdf$IVshort,esdf$Externalizing)
```

```
##
##
##    Cell Contents
## |-------------------------|
## |                       N |
## | Chi-square contribution |
## |           N / Row Total |
## |           N / Col Total |
## |         N / Table Total |
## |-------------------------|
##
##
## Total Observations in Table:  120
##
##
##              | esdf$Externalizing
## esdf$IVshort |     FALSE |      TRUE | Row Total |
## -------------|-----------|-----------|-----------|
##       Income |        12 |         8 |        20 |
##              |     0.167 |     0.190 |           |
##              |     0.600 |     0.400 |     0.167 |
##              |     0.188 |     0.143 |           |
##              |     0.100 |     0.067 |           |
## -------------|-----------|-----------|-----------|
## Hollingshead |         4 |         5 |         9 |
##              |     0.133 |     0.152 |           |
```

```
##               |     0.444 |     0.556 |     0.075 |
##               |     0.062 |     0.089 |           |
##               |     0.033 |     0.042 |           |
## -------------|-----------|-----------|-----------|
##   Parent Ed. |        17 |        14 |        31 |
##               |     0.013 |     0.015 |           |
##               |     0.548 |     0.452 |     0.258 |
##               |     0.266 |     0.250 |           |
##               |     0.142 |     0.117 |           |
## -------------|-----------|-----------|-----------|
##      Poverty |        16 |        15 |        31 |
##               |     0.017 |     0.020 |           |
##               |     0.516 |     0.484 |     0.258 |
##               |     0.250 |     0.268 |           |
##               |     0.133 |     0.125 |           |
## -------------|-----------|-----------|-----------|
##   Assistance |        13 |        13 |        26 |
##               |     0.054 |     0.062 |           |
##               |     0.500 |     0.500 |     0.217 |
##               |     0.203 |     0.232 |           |
##               |     0.108 |     0.108 |           |
## -------------|-----------|-----------|-----------|
##   Subjective |         2 |         1 |         3 |
##               |     0.100 |     0.114 |           |
##               |     0.667 |     0.333 |     0.025 |
##               |     0.031 |     0.018 |           |
##               |     0.017 |     0.008 |           |
## -------------|-----------|-----------|-----------|
## Column Total |        64 |        56 |       120 |
##               |     0.533 |     0.467 |           |
## -------------|-----------|-----------|-----------|
##
##
```

The 2 moderator (Full) model has a lower (more negative) AIC and high log likelihood, with a sig. wald test vs the un-moderated, omnibus model.

The interaction (full) model has about the same AIC (worse AICc and BIC) and a significant likelihood test with respect to the 2 moderator model. The cell counts in the interaction model are rather small (TRUE = Externalizing):

	FALSE	TRUE
Income	12	8
Hollingshead	4	5
Parent Ed.	17	14
Poverty	16	15
Assistance	13	13
Subjective	2	1

A model incorporating both SES Measure and internalizing describes the data better than the un-moderated model. It's somewhat ambiguous whether an interaction model is superior to a model which merely models both moderators. We will go with the more parsimonious two moderator model. For interested readers, a summary of the interaction model is presented under the 'Supplemental Analyses' section at the end of the document.

10.3.1 Final Model

```
m.combined.intext.IV<-rma.mv(yi=gcor,
                         V=g.v,
                         mods= ~ IVshort+Externalizing,
                         random=~1 | study.ID/efid,
                         slab=paste(study.ID, efid,Externalizing,sep=" "),
                         data=esdf
                         )

m.combined.intext.IV.coresthigh<-rma.mv(yi=gcor,
                         V=clubSandwich::impute_covariance_matrix(esdf$g.v,esdf$study.ID,coresthigh),
                         mods= ~ IVshort+Externalizing,
                         random=~1 | study.ID/efid,
                         slab=paste(study.ID, efid,Externalizing,sep=" "),
                         data=esdf
                         )

summary(m.combined.intext.IV)
```

```
##
## Multivariate Meta-Analysis Model (k = 120; method: REML)
##
##    logLik  Deviance       AIC       BIC      AICc
##   44.8946  -89.7892  -71.7892  -47.2427  -70.0416
##
```

```
## Variance Components:
##
##              estim    sqrt  nlvls  fixed         factor
## sigma^2.1  0.0151  0.1228     16     no       study.ID
## sigma^2.2  0.0058  0.0761    120     no  study.ID/efid
##
## Test for Residual Heterogeneity:
## QE(df = 113) = 367.6400, p-val < .0001
##
## Test of Moderators (coefficient(s) 2:7):
## QM(df = 6) = 17.7472, p-val = 0.0069
##
## Model Results:
##
##                      estimate      se    zval    pval    ci.lb   ci.ub
## intrcpt                0.1649  0.0452  3.6518  0.0003   0.0764  0.2534  ***
## IVshortHollingshead    0.0217  0.0683  0.3171  0.7512  -0.1122  0.1556
## IVshortParent Ed.      0.0628  0.0368  1.7061  0.0880  -0.0093  0.1350    .
## IVshortPoverty         0.0579  0.0352  1.6461  0.0998  -0.0111  0.1269    .
## IVshortAssistance      0.1286  0.0378  3.4015  0.0007   0.0545  0.2027  ***
## IVshortSubjective      0.0486  0.0675  0.7209  0.4710  -0.0836  0.1809
## ExternalizingTRUE      0.0558  0.0258  2.1668  0.0302   0.0053  0.1063    *
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
summary(m.combined.intext.IV.coresthigh)
```

```
##
## Multivariate Meta-Analysis Model (k = 120; method: REML)
##
##   logLik  Deviance       AIC       BIC      AICc
##  47.1795  -94.3591  -76.3591  -51.8126  -74.6115
##
## Variance Components:
##
##              estim    sqrt  nlvls  fixed         factor
## sigma^2.1  0.0130  0.1142     16     no       study.ID
## sigma^2.2  0.0068  0.0823    120     no  study.ID/efid
##
```

```
## Test for Residual Heterogeneity:
## QE(df = 113) = 331.5183, p-val < .0001
##
## Test of Moderators (coefficient(s) 2:7):
## QM(df = 6) = 18.4022, p-val = 0.0053
##
## Model Results:
##
##                        estimate      se    zval    pval    ci.lb   ci.ub
## intrcpt                  0.1685  0.0441  3.8253  0.0001   0.0822  0.2549  ***
## IVshortHollingshead      0.0179  0.0656  0.2721  0.7855  -0.1108  0.1465
## IVshortParent Ed.        0.0544  0.0364  1.4960  0.1347  -0.0169  0.1256
## IVshortPoverty           0.0548  0.0346  1.5822  0.1136  -0.0131  0.1226
## IVshortAssistance        0.1273  0.0377  3.3761  0.0007   0.0534  0.2011  ***
## IVshortSubjective        0.0253  0.0769  0.3294  0.7418  -0.1254  0.1760
## ExternalizingTRUE        0.0573  0.0250  2.2940  0.0218   0.0083  0.1062    *
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
confint(m.combined.intext.IV)
```

```
## [[1]]
##
##            estimate  ci.lb  ci.ub
## sigma^2.1   0.0151 0.0064 0.0385
## sigma.1     0.1228 0.0803 0.1962
##
##
## [[2]]
##
##            estimate  ci.lb  ci.ub
## sigma^2.2   0.0058 0.0031 0.0101
## sigma.2     0.0761 0.0558 0.1007
```

```r
confint(m.combined.intext.IV.coresthigh)
```

```
## [[1]]
##
##            estimate  ci.lb  ci.ub
```

```
## sigma^2.1   0.0130 0.0043 0.0364
## sigma.1     0.1142 0.0658 0.1907
##
##
## [[2]]
##
##           estimate  ci.lb  ci.ub
## sigma^2.2   0.0068 0.0040 0.0112
## sigma.2     0.0823 0.0633 0.1057
```

```
pander(comptable(list(m.combined.intext.IV,m.combined.intext.IV.coresthigh),
          c("none","high")))
```

	none	high	diff
intrcpt	0.16	0.17	0.0036
IVshortHollingshead	0.022	0.018	-0.0038
IVshortParent Ed.	0.063	0.054	-0.0084
IVshortPoverty	0.058	0.055	-0.0032
IVshortAssistance	0.13	0.13	-0.0013
IVshortSubjective	0.049	0.025	-0.023
ExternalizingTRUE	0.056	0.057	0.0015
int.ci.l	0.076	0.082	0.0058
int.ci.u	0.25	0.25	0.0015
s2between	0.015	0.013	-0.002
s2within	0.0058	0.0068	0.00098

11 SES clustered models

As noted previously, comparing all effects in the same parameter (standard mean difference) allows for maximal power and ability to model moderation. However, that approach makes some assumptions about the underlying data which are not certain, and yields effect sizes that are not always interpretable (for example correlation between two continuous variables is easily understood, whereas standard mean difference between the same does not since there are not necessarily two groups). We therefore also present these bivariate models in their proper effect parameters:

```
contextcols<-c("efid","study.ID","n","IVshort","DVshort","p.entered")
ORcols<-c("lOR","lOR.v")
Gcols<-c("g","g.v")
Rcols<-c("Zr","Zr.v")
```

11.1 Parent Education (continuous)

	efid	study.ID	n	IVshort	DVshort	p.entered	g	g.v
4	4	GSM	1420	Parent Ed.	Ext.	g	0.11	0.051
49	49	PHDCN	2805	Parent Ed.	Int.	Zr	0.3	0.0015
72	72	PYS.y	503	Parent Ed.	Dep.	lOR	0.22	0.018
91	91	CIC	776	Parent Ed.	Int.	g	0.44	0.014
95	95	CIC	776	Parent Ed.	Ext.	g	0.58	0.014
99	99	FF	1588	Parent Ed.	Ext.	g	0.076	0.0046
103	103	FF	2259	Parent Ed.	Ext. w2	g	0.25	0.0039
107	107	FF	2259	Parent Ed.	Int. w2	g	0.24	0.0039
115	115	PSID.CDS2	1409	Parent Ed.	Dep.	g	0.08	0.0054
119	119	PSID.CDS2014	1064	Parent Ed.	Dep.	g	0.23	0.0092

```
select.PEbySymp<-esdf$IV=="Parental Ed" & esdf$Continuous==TRUE
m.PEbySymp<-rma.mv(yi=g,
                         V=g.v,
                         random=~1 | study.ID/efid,
                         slab=paste(study.ID, efid,sep=" "),
                         data=esdf[select.PEbySymp,]
                         )

m.PEbySymp.coresthigh<-rma.mv(yi=g,
                         V=with(esdf[select.PEbySymp,],
                                clubSandwich::impute_covariance_matrix(g.v,study.ID,coresthigh)),
                         random=~1 | study.ID/efid,
                         slab=paste(study.ID, efid,sep=" "),
                         data=esdf[select.PEbySymp,]
                         )

summary(m.PEbySymp)
```

```
##
## Multivariate Meta-Analysis Model (k = 10; method: REML)
##
##    logLik  Deviance       AIC       BIC      AICc
##    4.8574   -9.7148   -3.7148   -3.1231    1.0852
```

```
##
## Variance Components:
##
##              estim    sqrt  nlvls  fixed         factor
## sigma^2.1  0.0113  0.1061      7     no       study.ID
## sigma^2.2  0.0030  0.0543     10     no  study.ID/efid
##
## Test for Heterogeneity:
## Q(df = 9) = 23.4758, p-val = 0.0052
##
## Model Results:
##
## estimate      se    zval    pval   ci.lb   ci.ub
##   0.2464  0.0553  4.4554  <.0001  0.1380  0.3548  ***
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
confint(m.PEbySymp)
```

```
## [[1]]
##
##            estimate  ci.lb  ci.ub
## sigma^2.1    0.0113 0.0000 0.0764
## sigma.1      0.1061 0.0000 0.2764
##
##
## [[2]]
##
##            estimate  ci.lb  ci.ub
## sigma^2.2    0.0030 0.0000 0.0410
## sigma.2      0.0543 0.0000 0.2024
```

```
pander(comptable(list(m.PEbySymp,m.PEbySymp.coresthigh),
          c("none","high")))
```

	none	high	diff
intrcpt	0.25	0.24	-0.0026
int.ci.l	0.14	0.14	0.0013
int.ci.u	0.35	0.35	-0.0066

	none	high	diff
s2between	0.011	0.0085	-0.0028
s2within	0.003	0.0043	0.0013

11.2 Parent Education (disordered)

	efid	study.ID	n	IVshort	DVshort	p.entered	lOR	lOR.v
10	10	GSM	1420	Parent Ed.	ADHD	lOR	1.4	2.5
11	11	GSM	1420	Parent Ed.	PTSD	lOR	1.6	102
12	12	GSM	1420	Parent Ed.	Dep.	lOR	-0.35	101
13	13	GSM	1420	Parent Ed.	Anx.	lOR	0.15	2.4
14	14	GSM	1420	Parent Ed.	DBD	lOR	1.1	0.93
17	17	MECA	984	Parent Ed.	ADHD	lOR	-0.12	0.37
21	21	MECA	984	Parent Ed.	Dep.	lOR	0.18	0.29
25	25	MECA	984	Parent Ed.	Anx.	lOR	0.41	0.099
29	29	MECA	984	Parent Ed.	DBD	lOR	0.35	0.18
32	32	NCSA	6483	Parent Ed.	PTSD	lOR	0	0.031
33	33	NCSA	6483	Parent Ed.	ADHD	lOR	0.53	0.048
37	37	NCSA	6483	Parent Ed.	Dep.	lOR	0	0.044
38	38	NCSA	6483	Parent Ed.	Anx.	lOR	0.53	0.018
39	39	NCSA	6483	Parent Ed.	DBD	lOR	0.41	0.063
52	52	PHDCN	2805	Parent Ed.	Int.	Zr	0.68	0.0052
67	67	PYS.y	503	Parent Ed.	DBD	lOR	0.41	0.061
68	68	PYS.o	506	Parent Ed.	DBD	lOR	0.79	0.065
75	75	CIC	776	Parent Ed.	ADHD	lOR	0.54	0.1
79	79	CIC	776	Parent Ed.	Dep.	lOR	0.56	0.31
83	83	CIC	776	Parent Ed.	Anx.	lOR	0.73	0.064
87	87	CIC	776	Parent Ed.	DBD	lOR	0.83	0.063

```
select.PEbyDis<-esdf$IV=="Parental Ed" & esdf$Continuous==FALSE
m.PEbyDis<-rma.mv(yi=lOR,
                  V=diag(lOR.v),
                  random=~1 | study.ID/efid,
                  slab=paste(study.ID, efid,sep=" "),
                  data=esdf[select.PEbyDis,]
```

```
                         )

m.PEbyDis.coresthigh<-rma.mv(yi=lOR,
                         V=with(esdf[select.PEbyDis,],
                                clubSandwich::impute_covariance_matrix(g.v,study.ID,coresthigh)),
                         random=~1 | study.ID/efid,
                         slab=paste(study.ID, efid,sep=" "),
                         data=esdf[select.PEbyDis,]
                         )

summary(m.PEbyDis)
```

```
##
## Multivariate Meta-Analysis Model (k = 21; method: REML)
##
##   logLik  Deviance       AIC       BIC      AICc
## -13.5395   27.0791   33.0791   36.0663   34.5791
##
## Variance Components:
##
##             estim    sqrt  nlvls  fixed         factor
## sigma^2.1  0.0232  0.1523      7     no       study.ID
## sigma^2.2  0.0158  0.1256     21     no  study.ID/efid
##
## Test for Heterogeneity:
## Q(df = 20) = 25.9820, p-val = 0.1664
##
## Model Results:
##
## estimate      se    zval    pval   ci.lb   ci.ub
##   0.5205  0.0966  5.3909  <.0001  0.3313  0.7097  ***
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
confint(m.PEbyDis)
```

```
## [[1]]
##
```

```
##            estimate  ci.lb  ci.ub
## sigma^2.1   0.0232 0.0000 0.2060
## sigma.1     0.1523 0.0000 0.4539
##
##
## [[2]]
##
##            estimate  ci.lb  ci.ub
## sigma^2.2   0.0158 0.0000 0.1128
## sigma.2     0.1256 0.0000 0.3359
```

```r
pander(comptable(list(m.PEbyDis,m.PEbyDis.coresthigh),
          c("none","high")))
```

	none	high	diff
intrcpt	0.52	0.52	0.0023
int.ci.l	0.33	0.34	0.006
int.ci.u	0.71	0.71	-0.0015
s2between	0.023	0.024	0.00092
s2within	0.016	0.035	0.02

11.3 Poverty Status (poverty line) (continuous)

	efid	study.ID	n	IVshort	DVshort	p.entered	g	g.v
3	3	GSM	1420	Poverty	Ext.	g	0.31	0.0033
47	47	PGS	1232	Poverty	DBD	g	0.36	0.0033
48	48	PGS	1232	Poverty	Dep.	g	0.21	0.0033
90	90	CIC	776	Poverty	Int.	g	0.48	0.0099
94	94	CIC	776	Poverty	Ext.	g	0.48	0.0099
98	98	FF	1589	Poverty	Ext.	g	0.21	0.0028
102	102	FF	2246	Poverty	Ext. w2	g	0.33	0.0021
106	106	FF	2246	Poverty	Int. w2	g	0.35	0.0021
114	114	PSID.CDS2	1455	Poverty	Dep.	g	0.053	0.0064
118	118	PSID.CDS2014	1045	Poverty	Dep.	g	0.019	0.008

```r
select.PVbySymp<-esdf$IV=="Poverty Status (poverty line)" & esdf$Continuous==TRUE
m.PVbySymp<-rma.mv(yi=g,
                        V=g.v,
                        random=~1 | study.ID/efid,
                        slab=paste(study.ID, efid,sep=" "),
                        data=esdf[select.PVbySymp,]
                        )

m.PVbySymp.coresthigh<-rma.mv(yi=g,
                        V=with(esdf[select.PVbySymp,],
                               clubSandwich::impute_covariance_matrix(g.v,study.ID,coresthigh)),
                        random=~1 | study.ID/efid,
                        slab=paste(study.ID, efid,sep=" "),
                        data=esdf[select.PVbySymp,]
                        )

summary(m.PVbySymp)
```

```
##
## Multivariate Meta-Analysis Model (k = 10; method: REML)
##
##   logLik  Deviance       AIC       BIC      AICc
##   5.1047  -10.2095   -4.2095   -3.6178    0.5905
##
## Variance Components:
##
##             estim    sqrt  nlvls  fixed         factor
## sigma^2.1  0.0188  0.1372      6     no       study.ID
## sigma^2.2  0.0039  0.0626     10     no  study.ID/efid
##
## Test for Heterogeneity:
## Q(df = 9) = 34.2193, p-val < .0001
##
## Model Results:
##
## estimate      se    zval    pval   ci.lb   ci.ub
##   0.2549  0.0650  3.9205  <.0001  0.1275  0.3823  ***
##
```

```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
confint(m.PVbySymp)
```

```
## [[1]]
##
##            estimate  ci.lb  ci.ub
## sigma^2.1   0.0188 0.0000 0.1250
## sigma.1     0.1372 0.0000 0.3535
##
##
## [[2]]
##
##            estimate  ci.lb  ci.ub
## sigma^2.2   0.0039 0.0000 0.0424
## sigma.2     0.0626 0.0000 0.2058
```

```r
pander(comptable(list(m.PVbySymp,m.PVbySymp.coresthigh),c("none","high")))
```

	none	high	diff
intrcpt	0.25	0.25	-0.0011
int.ci.l	0.13	0.13	3e-04
int.ci.u	0.38	0.38	-0.0024
s2between	0.019	0.017	-0.0014
s2within	0.0039	0.0047	0.00073

11.4 Poverty Status (poverty line) (disordered)

	efid	study.ID	n	IVshort	DVshort	p.entered	lOR	lOR.v
5	5	GSM	1420	Poverty	ADHD	lOR	0.21	0.24
6	6	GSM	1420	Poverty	PTSD	lOR	-2.6	102
7	7	GSM	1420	Poverty	Dep.	lOR	-0.46	2.7
8	8	GSM	1420	Poverty	Anx.	lOR	0.96	0.063
9	9	GSM	1420	Poverty	DBD	lOR	1.1	0.048
15	15	MECA	970	Poverty	ADHD	lOR	-0.19	0.17
19	19	MECA	970	Poverty	Dep.	lOR	0.34	0.12
23	23	MECA	970	Poverty	Anx.	lOR	0.4	0.046

	efid	study.ID	n	IVshort	DVshort	p.entered	lOR	lOR.v
27	27	MECA	970	Poverty	DBD	lOR	0.6	0.074
34	34	NCSA	6483	Poverty	Dep.	lOR	0	0.063
35	35	NCSA	6483	Poverty	Anx.	lOR	0.26	0.022
36	36	NCSA	6483	Poverty	DBD	lOR	0.18	0.037
43	43	NHANES	3081	Poverty	DBD	lOR	0.4	0.067
44	44	NHANES	3081	Poverty	ADHD	lOR	0.24	0.011
45	45	NHANES	4150	Poverty	Dep.	lOR	0.015	0.034
55	55	PHDCN	2810	Poverty	Int.	lOR	0.47	0.0048
56	56	PHDCN	2810	Poverty	Ext.	lOR	0.64	0.01
74	74	CIC	776	Poverty	ADHD	lOR	0.86	0.066
78	78	CIC	776	Poverty	Dep.	lOR	1.5	0.17
82	82	CIC	776	Poverty	Anx.	lOR	0.72	0.046
86	86	CIC	776	Poverty	DBD	lOR	1.1	0.043

```
select.PVbyDis<-esdf$IV=="Poverty Status (poverty line)" & esdf$Continuous==FALSE
m.PVbyDis<-rma.mv(yi=lOR,
                         V=diag(lOR.v),
                         random=~1 | study.ID/efid,
                         slab=paste(study.ID, efid,sep=" "),
                         data=esdf[select.PVbyDis,]
                         )

m.PVbyDis.coresthigh<-rma.mv(yi=lOR,
                         V=with(esdf[select.PVbyDis,],
                                clubSandwich::impute_covariance_matrix(g.v,study.ID,coresthigh)),
                         random=~1 | study.ID/efid,
                         slab=paste(study.ID, efid,sep=" "),
                         data=esdf[select.PVbyDis,]
                         )

summary(m.PVbyDis)
```

```
##
## Multivariate Meta-Analysis Model (k = 21; method: REML)
##
##   logLik  Deviance       AIC       BIC      AICc
```

```
##  -9.5875   19.1750   25.1750   28.1622   26.6750
##
## Variance Components:
##
##                estim    sqrt  nlvls  fixed         factor
## sigma^2.1  0.1036  0.3219      6     no       study.ID
## sigma^2.2  0.0015  0.0389     21     no  study.ID/efid
##
## Test for Heterogeneity:
## Q(df = 20) = 57.4314, p-val < .0001
##
## Model Results:
##
## estimate      se    zval    pval   ci.lb   ci.ub
##   0.5270  0.1399  3.7662  0.0002  0.2527  0.8012  ***
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
confint(m.PVbyDis)
```

```
## [[1]]
##
##           estimate  ci.lb  ci.ub
## sigma^2.1   0.1036 0.0264 0.5528
## sigma.1     0.3219 0.1625 0.7435
##
##
## [[2]]
##
##           estimate  ci.lb  ci.ub
## sigma^2.2   0.0015 0.0000 0.0549
## sigma.2     0.0389 0.0000 0.2342
```

```r
pander(comptable(list(m.PVbyDis,m.PVbyDis.coresthigh),c("none","high")))
```

	none	high	diff
intrcpt	0.53	0.52	-0.0026
int.ci.l	0.25	0.24	-0.014
int.ci.u	0.8	0.81	0.0092

	none	high	diff
s2between	0.1	0.1	-0.0016
s2within	0.0015	0.053	0.052

11.5 Receipt of Public Assistance (continuous)

	efid	study.ID	n	IVshort	DVshort	p.entered	g	g.v
51	51	PHDCN	2805	Assistance	Int.	Zr	0.18	0.0015
70	70	PYS.y	503	Assistance	Dep.	lOR	0.35	0.023
71	71	PYS.m	508	Assistance	Dep.	lOR	0.29	0.032
92	92	CIC	776	Assistance	Int.	g	0.69	0.028
96	96	CIC	776	Assistance	Ext.	g	0.48	0.028
100	100	FF	1589	Assistance	Ext.	g	0.3	0.0028
104	104	FF	2282	Assistance	Ext. w2	g	0.42	0.0052
108	108	FF	2282	Assistance	Int. w2	g	0.4	0.0052
111	111	NSPC	823	Assistance	Ext.	Zr	0.3	0.0052
112	112	NSPC	823	Assistance	Int.	Zr	-0.02	0.0049
116	116	PSID.CDS2	1452	Assistance	Dep.	g	0.1	0.0072
120	120	PSID.CDS2014	1045	Assistance	Dep.	g	0.08	0.0059

```
select.PAbySymp<-esdf$IV=="Receipt of Public Assistance" & esdf$Continuous==TRUE
m.PAbySymp<-rma.mv(yi=g,
                         V=g.v,
                         random=~1 | study.ID/efid,
                         slab=paste(study.ID, efid,sep=" "),
                         data=esdf[select.PAbySymp,]
                         )

m.PAbySymp.coresthigh<-rma.mv(yi=g,
                         V=with(esdf[select.PAbySymp,],
                                clubSandwich::impute_covariance_matrix(g.v,study.ID,coresthigh)),
                         random=~1 | study.ID/efid,
                         slab=paste(study.ID, efid,sep=" "),
                         data=esdf[select.PAbySymp,]
                         )
```

```r
summary(m.PAbySymp)
```

```
##
## Multivariate Meta-Analysis Model (k = 12; method: REML)
##
##   logLik  Deviance       AIC       BIC      AICc
##   3.2961   -6.5922   -0.5922    0.6015    2.8364
##
## Variance Components:
##
##             estim    sqrt  nlvls  fixed         factor
## sigma^2.1  0.0136  0.1165      8     no       study.ID
## sigma^2.2  0.0111  0.1052     12     no  study.ID/efid
##
## Test for Heterogeneity:
## Q(df = 11) = 45.8283, p-val < .0001
##
## Model Results:
##
## estimate      se    zval    pval   ci.lb   ci.ub
##   0.2554  0.0607  4.2064  <.0001  0.1364  0.3744  ***
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
confint(m.PAbySymp)
```

```
## [[1]]
##
##           estimate  ci.lb  ci.ub
## sigma^2.1   0.0136 0.0000 0.0903
## sigma.1     0.1165 0.0000 0.3005
##
##
## [[2]]
##
##           estimate  ci.lb  ci.ub
## sigma^2.2   0.0111 0.0003 0.0660
## sigma.2     0.1052 0.0164 0.2569
```

```r
pander(comptable(list(m.PAbySymp,m.PAbySymp.coresthigh),c("none","high")))
```

	none	high	diff
intrcpt	0.26	0.25	-0.0035
int.ci.l	0.14	0.14	0.00012
int.ci.u	0.37	0.37	-0.0071
s2between	0.014	0.01	-0.0031
s2within	0.011	0.012	0.0013

11.6 Receipt of Public Assistance (disordered)

	efid	study.ID	n	IVshort	DVshort	p.entered	lOR	lOR.v
18	18	MECA	290	Assistance	ADHD	lOR	0.88	0.35
22	22	MECA	290	Assistance	Dep.	lOR	0.49	0.2
26	26	MECA	290	Assistance	Anx.	lOR	0.35	0.11
30	30	MECA	290	Assistance	DBD	lOR	1.4	0.14
46	46	PGS	2393	Assistance	DBD	lOR	1.3	0.013
54	54	PHDCN	2805	Assistance	Int.	Zr	0.24	0.0048
61	61	PYS.y	503	Assistance	ADHD	lOR	0.53	0.052
64	64	PYS.y	503	Assistance	DBD	lOR	0.79	0.065
65	65	PYS.m	508	Assistance	DBD	lOR	0.53	0.1
66	66	PYS.o	506	Assistance	DBD	lOR	0.83	0.073
76	76	CIC	776	Assistance	ADHD	lOR	1.2	0.14
80	80	CIC	776	Assistance	Dep.	lOR	1.4	0.33
84	84	CIC	776	Assistance	Anx.	lOR	1.1	0.11
88	88	CIC	776	Assistance	DBD	lOR	0.94	0.12

```r
select.PAbyDis<-esdf$IV=="Receipt of Public Assistance" & esdf$Continuous==FALSE
m.PAbyDis<-rma.mv(yi=lOR,
                         V=diag(lOR.v),
                         random=~1 | study.ID/efid,
                         slab=paste(study.ID, efid,sep=" "),
                         data=esdf[select.PAbyDis,]
                         )
```

```r
m.PAbyDis.coresthigh<-rma.mv(yi=lOR,
                         V=with(esdf[select.PAbyDis,],
                                clubSandwich::impute_covariance_matrix(g.v,study.ID,coresthigh)),
                         random=~1 | study.ID/efid,
                         slab=paste(study.ID, efid,sep=" "),
                         data=esdf[select.PAbyDis,]
                         )

summary(m.PAbyDis)
```

```
##
## Multivariate Meta-Analysis Model (k = 14; method: REML)
##
##   logLik  Deviance       AIC       BIC      AICc
##  -6.6482   13.2965   19.2965   20.9913   21.9631
##
## Variance Components:
##
##             estim    sqrt  nlvls  fixed         factor
## sigma^2.1  0.1176  0.3429      7     no       study.ID
## sigma^2.2  0.0014  0.0374     14     no  study.ID/efid
##
## Test for Heterogeneity:
## Q(df = 13) = 74.8067, p-val < .0001
##
## Model Results:
##
## estimate      se    zval    pval   ci.lb   ci.ub
##   0.7632  0.1493  5.1131  <.0001  0.4706  1.0557  ***
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
confint(m.PAbyDis)
```

```
## [[1]]
##
##           estimate  ci.lb  ci.ub
## sigma^2.1   0.1176 0.0000 0.5324
```

```
## sigma.1     0.3429 0.0000 0.7297
##
##
## [[2]]
##
##            estimate  ci.lb  ci.ub
## sigma^2.2   0.0014 0.0000 0.2926
## sigma.2     0.0374 0.0000 0.5409
```

```
pander(comptable(list(m.PAbyDis,m.PAbyDis.coresthigh),c("none","high")))
```

	none	high	diff
intrcpt	0.76	0.79	0.031
int.ci.l	0.47	0.56	0.084
int.ci.u	1.1	1	-0.022
s2between	0.12	0.028	-0.089
s2within	0.0014	0.095	0.094

11.7 Family Income (continuous)

	efid	study.ID	n	IVshort	DVshort	p.entered	g	g.v
50	50	PHDCN	2805	Income	Int.	Zr	-0.094	0.0014
57	57	PHDCN	1517	Income	Int.	Zr	-0.14	0.0027
58	58	PHDCN	1517	Income	Ext.	Zr	-0.06	0.0026
89	89	CIC	771	Income	Int.	Zr	-0.43	0.0059
93	93	CIC	771	Income	Ext.	Zr	-0.37	0.0058
97	97	FF	1589	Income	Ext.	Zr	-0.16	0.0026
101	101	FF	2257	Income	Ext. w2	Zr	-0.27	0.0019
105	105	FF	2230	Income	Int. w2	Zr	-0.22	0.0019
113	113	PSID.CDS2	1455	Income	Dep.	Zr	0.022	0.0028
117	117	PSID.CDS2014	1045	Income	Dep.	Zr	-0.0082	0.0038

```
select.INCbySymp<-esdf$IV=="Family Income" & esdf$Continuous==TRUE
m.INCbySymp<-rma.mv(yi=Zr,
                        V=Zr.v,
```

```r
                        random=~1 | study.ID/efid,
                        slab=paste(study.ID, efid,sep=" "),
                        data=esdf[select.INCbySymp,]
                        )

m.INCbySymp.coresthigh<-rma.mv(yi=Zr,
                        V=with(esdf[select.INCbySymp,],
                               clubSandwich::impute_covariance_matrix(Zr.v,study.ID,coresthigh)),
                        random=~1 | study.ID/efid,
                        slab=paste(study.ID, efid,sep=" "),
                        data=esdf[select.INCbySymp,]
                        )

summary(m.INCbySymp)
```

```
##
## Multivariate Meta-Analysis Model (k = 10; method: REML)
##
##   logLik  Deviance       AIC       BIC      AICc
##  14.8793  -29.7586  -23.7586  -23.1670  -18.9586
##
## Variance Components:
##
##             estim    sqrt  nlvls  fixed         factor
## sigma^2.1  0.0064  0.0802      5     no       study.ID
## sigma^2.2  0.0000  0.0000     10     no  study.ID/efid
##
## Test for Heterogeneity:
## Q(df = 9) = 54.4203, p-val < .0001
##
## Model Results:
##
## estimate      se     zval    pval    ci.lb   ci.ub
##  -0.0708  0.0373  -1.8999  0.0575  -0.1438  0.0022  .
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
confint(m.INCbySymp)
```

```
## [[1]]
##
##             estimate  ci.lb  ci.ub
## sigma^2.1   0.0064 0.0016 0.0420
## sigma.1     0.0802 0.0397 0.2050
##
##
## [[2]]
##
##             estimate  ci.lb  ci.ub
## sigma^2.2   0.0000 0.0000 0.0020
## sigma.2     0.0000 0.0000 0.0442
```

```r
pander(comptable(list(m.INCbySymp,m.INCbySymp.coresthigh),c("none","high")))
```

	none	high	diff
intrcpt	-0.071	-0.07	0.00035
int.ci.l	-0.14	-0.14	0.00062
int.ci.u	0.0022	0.0023	7.1e-05
s2between	0.0064	0.0062	-0.00018
s2within	2e-12	8.3e-05	8.3e-05

11.8 Family Income (disordered)

	efid	study.ID	n	IVshort	DVshort	p.entered	g	g.v
16	16	MECA	970	Income	ADHD	g2	-0.2	0.018
20	20	MECA	970	Income	Dep.	g2	-0.17	0.017
24	24	MECA	970	Income	Anx.	g2	-0.18	0.0062
28	28	MECA	970	Income	DBD	g2	-0.39	0.012
31	31	NCSA	6483	Income	PTSD	lOR	0.14	0.017
53	53	PHDCN	2805	Income	Int.	Zr	-0.33	0.0015
73	73	CIC	771	Income	ADHD	g2	-0.4	0.012
77	77	CIC	771	Income	Dep.	g2	-0.56	0.042
81	81	CIC	771	Income	Anx.	g2	-0.38	0.0075
85	85	CIC	771	Income	DBD	g2	-0.45	0.0074

We need to reverse code the NCSA income effect, as income was coded as <3 PIR.

```
esdf[esdf$efid=="31","g"]<-esdf[esdf$efid=="31","g"]*-1

select.INCbyDis<-esdf$IV=="Family Income" & esdf$Continuous==FALSE
m.INCbyDis<-rma.mv(yi=g,
                         V=diag(g.v),
                         random=~1 | study.ID/efid,
                         slab=paste(study.ID, efid,sep=" "),
                         data=esdf[select.INCbyDis,]
                         )

m.INCbyDis.coresthigh<-rma.mv(yi=g,
                         V=with(esdf[select.INCbyDis,],
                                clubSandwich::impute_covariance_matrix(g.v,study.ID,coresthigh)),
                         random=~1 | study.ID/efid,
                         slab=paste(study.ID, efid,sep=" "),
                         data=esdf[select.INCbyDis,]
                         )

summary(m.INCbyDis)
```

```
##
## Multivariate Meta-Analysis Model (k = 10; method: REML)
##
##   logLik  Deviance       AIC       BIC      AICc
##   7.0566  -14.1131   -8.1131   -7.5215   -3.3131
##
## Variance Components:
##
##              estim    sqrt  nlvls  fixed         factor
## sigma^2.1  0.0064  0.0801      4     no       study.ID
## sigma^2.2  0.0000  0.0000     10     no  study.ID/efid
##
## Test for Heterogeneity:
## Q(df = 9) = 12.1170, p-val = 0.2068
##
## Model Results:
##
## estimate      se     zval    pval    ci.lb    ci.ub
```

```
##  -0.3054  0.0508  -6.0146  <.0001  -0.4050  -0.2059  ***
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
confint(m.INCbyDis)
```

```
## [[1]]
##
##            estimate  ci.lb  ci.ub
## sigma^2.1    0.0064 0.0000 0.1000
## sigma.1      0.0801 0.0000 0.3162
##
##
## [[2]]
##
##            estimate  ci.lb  ci.ub
## sigma^2.2    0.0000 0.0000 0.0173
## sigma.2      0.0000 0.0000 0.1315
```

```r
pander(comptable(list(m.INCbyDis,m.INCbyDis.coresthigh),c("none","high")))
```

	none	high	diff
intrcpt	-0.31	-0.3	7e-04
int.ci.l	-0.4	-0.39	0.013
int.ci.u	-0.21	-0.22	-0.012
s2between	0.0064	0.0033	-0.0031
s2within	6.5e-12	1.5e-11	8.3e-12

11.9 Hollingshead (continuous)

	efid	study.ID	n	IVshort	DVshort	p.entered	Zr	Zr.v
1	1	CDP	585	Hollingshead	Ext.	Zr	-0.23	0.0017
2	2	CDP	585	Hollingshead	Int.	Zr	-0.12	0.0017
69	69	PYS.y	503	Hollingshead	Dep.	lOR	0.13	0.0059
109	109	NSPC	823	Hollingshead	Ext.	Zr	0	0.0012
110	110	NSPC	823	Hollingshead	Int.	Zr	-0.039	0.0012

Hollingshead index is usually represented as a continous variable - here it's only dichotomized in PYS. This should be analyzed by Zr. It was reverse coded in the latter three effects, so that should be corrected.

```
esdf[c(69,109,110),"Zr"]<-esdf[c(69,109,110),"Zr"]*-1
select.HollbySymp<-esdf$IV=="Hollingshead" & esdf$Continuous==TRUE
m.HollbySymp<-rma.mv(yi=Zr,
                         V=Zr.v,
                         random=~1 | study.ID/efid,
                         slab=paste(study.ID, efid,sep=" "),
                         data=esdf[select.HollbySymp,]
                         )

m.HollbySymp.coresthigh<-rma.mv(yi=Zr,
                         V=with(esdf[select.HollbySymp,],
                                clubSandwich::impute_covariance_matrix(Zr.v,study.ID,coresthigh)),
                         random=~1 | study.ID/efid,
                         slab=paste(study.ID, efid,sep=" "),
                         data=esdf[select.HollbySymp,]
                         )

summary(m.HollbySymp)
```

```
##
## Multivariate Meta-Analysis Model (k = 5; method: REML)
##
##   logLik  Deviance       AIC       BIC      AICc
##   3.9856   -7.9712   -1.9712   -3.8123   22.0288
##
## Variance Components:
##
##               estim    sqrt  nlvls  fixed         factor
## sigma^2.1  0.0101  0.1007      3     no       study.ID
## sigma^2.2  0.0016  0.0405      5     no  study.ID/efid
##
## Test for Heterogeneity:
## Q(df = 4) = 31.5092, p-val < .0001
##
## Model Results:
##
## estimate      se     zval    pval    ci.lb   ci.ub
```

```
##  -0.0904  0.0663  -1.3643  0.1725  -0.2203  0.0395
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
confint(m.HollbySymp)
```

```
## [[1]]
##
##            estimate  ci.lb  ci.ub
## sigma^2.1    0.0101 0.0000 0.2094
## sigma.1      0.1007 0.0000 0.4576
##
##
## [[2]]
##
##            estimate  ci.lb  ci.ub
## sigma^2.2    0.0016 0.0000 0.0402
## sigma.2      0.0405 0.0000 0.2005
```

```r
pander(comptable(list(m.HollbySymp,m.HollbySymp.coresthigh),c("none","high")))
```

	none	high	diff
intrcpt	-0.09	-0.09	0.00025
int.ci.l	-0.22	-0.22	8.6e-05
int.ci.u	0.039	0.04	4e-04
s2between	0.01	0.0097	-0.00045
s2within	0.0016	0.0022	0.00053

11.10 Hollingshead (disordered)

	efid	study.ID	n	IVshort	DVshort	p.entered	lOR	lOR.v
59	59	PYS	1509	Hollingshead	Dep.	lOR	0.53	0.039
60	60	PYS.m	508	Hollingshead	ADHD	lOR	0.47	0.082
62	62	PYS.m	508	Hollingshead	DBD	lOR	0.69	0.089
63	63	PYS.o	506	Hollingshead	DBD	lOR	0.41	0.061

All of these effects are from the Pittsburgh Youth Study, so there is no meta-analysis to be done here. Effects are described qualitatively above in supplementary results.

11.11 Effects from Subjective Social Status

SSS was only reported in NCSA-R and these effects are described qualitatively above in supplementary results.

	efid	study.ID	n	IVshort	DVshort	p.entered	lOR	lOR.v
40	40	NCSA	6483	Subjective	Dep.	lOR	-0.22	0.0012
41	41	NCSA	6483	Subjective	Anx.	lOR	-0.22	9e-04
42	42	NCSA	6483	Subjective	DBD	lOR	-0.36	0.0012

These are ORs associated with a one unit increase. The effect is about the same on depression / anxiety and larger on externalizing.

12 Figures

We are going to make figures using the 'forestplot' library (Gordon & Lumley, 2017).

For some of our plots, we are going to want multiple models displayed per plot. For example, for 'dichotomous SES on symptoms' we want all of our SES by symptom models stacked in to one figure, with the same axis. We will need about 9 forest plots, so it will be easier to functionalize this. We need one function (get_rma_data) per model (to extract the relevant data from each model and format it for the forestplot function). We need a second function that runs the first on a list of models and combines the returned data frames. A final function actually generates the forestplot. Then we can run each plot very simply with a few lines of code.

12.1 Plotting Functions: component models

```
get_rma_data<-function(rmamodel) {
  efids<-as.numeric(levels(rmamodel$mf.r.f[[1]]$efid)) #Get the id numbers of the effects included in the specified model.
  wi <- 1/sqrt(rmamodel$vi) #get a vector of weights
  psize<-wi/sum(wi,na.rm=TRUE) #calculate point size:
  psize<-(psize - min(psize, na.rm = TRUE))/(max(psize,na.rm = TRUE) - min(psize, na.rm = TRUE))
  psize <- (psize * 1) + 0.5
  #build a data frame for this model with all the stuff we want to display:
  df<-with(rmamodel,data.frame(Paper=as.character(esdf[efids,"cite"]), #name of paper
                              Cohort=as.character(esdf[efids,"study.ID"]), #name of Cohort
                              n=as.character(esdf[efids,"n"]), #effect n
                              DV=esdf[efids,"DVshort"], #dependent variable
```

```
                              mean=yi, #effect
                              lower=yi-1.96*sqrt(vi), #lower CI
                              upper=yi+1.96*sqrt(vi), #upper CI
                              sum=FALSE, #these are not summary ariables.
                              psize=psize, #insert the point size
                              stringsAsFactors = FALSE)) #don't factorize
  df<-df[order(df$DV),] #order the df by dependent variable
  df$DV<-as.character(df$DV)  #convert DV back to a string.
  pred<-predict(rmamodel) #Get predictions from the model
  #Now we use the pred object to get our summary statistics:
  rbind(df,data.frame(Paper=c("RE Model","Precision Interval"),
                      Cohort=NA,
                      n=NA,
                      #pwhite=NA,
                      #mage=NA,
                      DV=NA,
                      mean=pred$pred,
                      lower=c(pred$ci.lb,pred$cr.lb),
                      upper=c(pred$ci.ub,pred$cr.ub),
                      sum=TRUE,
                      psize=c(1,.5),
                      stringsAsFactors = FALSE))
}

#output from this function looks like this:
#                       Paper Cohort    n            DV      mean       lower     upper   sum     psize
#2        Loeber et al., 1998   PYS.y  503    Depression 0.3533426  0.05564357 0.6510416 FALSE 0.5464616
#3        Loeber et al., 1998   PYS.m  508    Depression 0.2921169 -0.05596824 0.6402019 FALSE 0.5000000
#1           Xue et al., 2005   PHDCN 2805 Internalizing 0.1835472  0.10857459 0.2585197 FALSE 1.5000000
#4  Cohen & Hesselbart, 1993*     CIC  776 Internalizing 0.6897441  0.36173323 1.0177551 FALSE 0.5168000
#5  Cohen & Hesselbart, 1993*     CIC  776 Externalizing 0.4802485  0.15317950 0.8073174 FALSE 0.5176390
#11                  RE Model    <NA> <NA>          <NA> 0.3303283  0.14011251 0.5205441  TRUE 1.0000000
#21        Precision Interval    <NA> <NA>          <NA> 0.3303283 -0.02121900 0.6818756  TRUE 0.5000000

get_rmalist_data<-function(mlist,tlist) {
  if(is.na(tlist)) {
    l<-lapply(mlist,get_rma_data) #make sure the input is in the right format
  } else {
```

```
    titles<-lapply(tlist,function(x) {data.frame(Paper=x, #generate subtitles
                    Cohort=NA,
                    n=NA,
                    #pwhite=NA,
                    #mage=NA,
                    DV=NA,
                    mean=NA,
                    lower=NA,
                    upper=NA,
                    sum=TRUE,
                    psize=FALSE)})
    models<-lapply(mlist,get_rma_data) #generate data by iterating get_rma_data across the relevant models
    idx<-order(c(seq_along(titles),seq_along(models))) #order by title and then model output
    l<-(c(titles,models))[idx]
  }
  df<-do.call("rbind",l)
  df
}

c_forestplot<-function(modellist,tlist=NA,para,transfexp=FALSE,...) {
  #Get Data
  plot.Data<-get_rmalist_data(modellist,tlist)

  #Transform if necessary.
  if(transfexp==TRUE) {
    plot.Data[,5:7]<-exp(plot.Data[,5:7])
  }

  #Format the Effect Summary line.
  effectnums<-plot.Data[,5:7]
  effectnums[plot.Data$Paper=="Precision Interval",1]<-NA
  effectnums[!is.na(effectnums$mean),"mchar"]<-numform::f_num(na.omit(effectnums$mean),digits=2)
  effectnums[!is.na(effectnums$lower),"lchar"]<-numform::f_num(na.omit(effectnums$lower),digits=2,p="[")
  effectnums[!is.na(effectnums$upper),"uchar"]<-numform::f_num(na.omit(effectnums$upper),digits=2,s="]")
  effectnums[effectnums$lower < -50 & !is.na(effectnums$lower),"lchar"]<-"[<-50.00"
  effectnums[effectnums$upper > 50 & !is.na(effectnums$upper),"uchar"]<-">50.00]"
  effectnums[is.na(effectnums)]<-""
  plot.Data$paratext<-with(effectnums,paste(mchar,lchar,uchar,sep=" "))
```

```r
#Add a header row
headers<-data.frame(Paper="Paper",
                    Cohort="Cohort",
                    n="n",
                    DV="Outcome",
                    mean=NA,
                    lower=NA,
                    upper=NA,
                    sum=TRUE,
                    psize=NA,
                    paratext=paste(para,"[95% CI]",sep=" "),
                    stringsAsFactors = FALSE)
plot.Data<-rbind(headers,plot.Data)

#Build a vector of our point shapes
#This is what makes the PI bar not a diamond.
sumfuncvector<-c(fpDrawBarCI,fpDrawBarCI)
for (i in 1:dim(plot.Data)[1]) {
  if(plot.Data[i,"Paper"]=="Precision Interval") {
         sumfuncvector[[i]]<-fpDrawBarCI
       } else {
         sumfuncvector[[i]]<-fpDrawSummaryCI
       }
}

#Build a list for where we want our lines.
subtitlerows<-which(is.na(plot.Data$lower))
hlineindices<-c(subtitlerows,subtitlerows+1)
hlines<-as.list(rep(TRUE,length(hlineindices)))
names(hlines)<-as.character(hlineindices)

forestplot(plot.Data[,c(1:4,10)],
           mean=plot.Data$mean,
           lower=plot.Data$lower,
           fn.ci_sum=sumfuncvector,
           upper=plot.Data$upper,
           is.summary=plot.Data$sum,
           align=c("l","l","c","l","r"),
```

```
             hrzl_lines = hlines,
             graph.pos=5,
             vertices=TRUE,
             colgap=unit(3,"mm"),
             boxsize=plot.Data$psize*.5,
             txt_gp=fpTxtGp(label=gpar(fontfamily="serif",fontsize="10")),
             graphwidth=unit(5,"cm"),
             mar=unit(rep(0,times=4),"mm"),
             ...) # feed any remaining args to the forestplot function
}
```

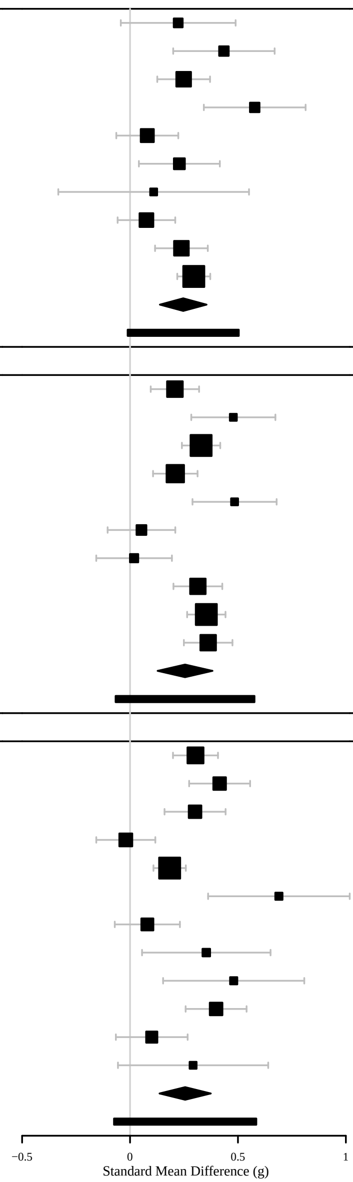
12.2 Dichotomous SES on symptoms.

The relevant models are:

- m.PEbySymp
- m.PVbySymp
- m.PAbySymp

```
#png("plot-dSESonSymp.png",width=7.5,height=9.5,units="in",res=dpi)
c_forestplot(list(m.PEbySymp,m.PVbySymp,m.PAbySymp),list("Parent Education","Poverty","Public Assistance"),"g",transfexp=FALSE,xlab="Stand
```

Paper	Cohort	n	Outcome	g [95% CI]
Parent Education				
Panel Study of Income Dynamics, 2020*	PSID.CDS2	1409	Dep.	.22 [−.04 .49]
Panel Study of Income Dynamics, 2020*	PSID.CDS2014	1064	Dep.	.44 [.20 .67]
Loeber et al., 1998	PYS.y	503	Dep.	.25 [.13 .37]
Costello et al., 1996*	GSM	1420	Ext.	.58 [.34 .81]
Cohen & Hesselbart, 1993*	CIC	776	Ext.	.08 [−.06 .22]
Waller, 2001*	FF	1588	Ext.	.23 [.04 .42]
Waller, 2001*	FF	2259	Ext. w2	.11 [−.33 .55]
Xue et al., 2005	PHDCN	2805	Int.	.08 [−.06 .21]
Cohen & Hesselbart, 1993*	CIC	776	Int.	.24 [.12 .36]
Waller, 2001*	FF	2259	Int. w2	.30 [.22 .37]
RE Model				**.25 [.14 .35]**
Precision Interval				**[−.01 .50]**
Poverty				
Panel Study of Income Dynamics, 2020*	PSID.CDS2	1455	Dep.	.21 [.10 .32]
Panel Study of Income Dynamics, 2020*	PSID.CDS2014	1045	Dep.	.48 [.28 .67]
Hipwell et al., 2011	PGS	1232	Dep.	.33 [.24 .42]
Hipwell et al., 2011	PGS	1232	DBD	.21 [.11 .31]
Costello et al., 1996*	GSM	1420	Ext.	.48 [.29 .68]
Cohen & Hesselbart, 1993*	CIC	776	Ext.	.05 [−.10 .21]
Waller, 2001*	FF	1589	Ext.	.02 [−.16 .19]
Waller, 2001*	FF	2246	Ext. w2	.31 [.20 .43]
Cohen & Hesselbart, 1993*	CIC	776	Int.	.35 [.26 .44]
Waller, 2001*	FF	2246	Int. w2	.36 [.25 .47]
RE Model				**.25 [.13 .38]**
Precision Interval				**[−.07 .58]**
Public Assistance				
Panel Study of Income Dynamics, 2020*	PSID.CDS2	1452	Dep.	.30 [.20 .41]
Panel Study of Income Dynamics, 2020*	PSID.CDS2014	1045	Dep.	.42 [.27 .56]
Loeber et al., 1998	PYS.y	503	Dep.	.30 [.16 .44]
Loeber et al., 1998	PYS.m	508	Dep.	−.02 [−.16 .12]
Waller, 2001*	FF	1589	Ext.	.18 [.11 .26]
McClure, 2007	NSPC	823	Ext.	.69 [.36 1.02]
Cohen & Hesselbart, 1993*	CIC	776	Ext.	.08 [−.07 .23]
Waller, 2001*	FF	2282	Ext. w2	.35 [.06 .65]
McClure, 2007	NSPC	823	Int.	.48 [.15 .81]
Xue et al., 2005	PHDCN	2805	Int.	.40 [.26 .54]
Cohen & Hesselbart, 1993*	CIC	776	Int.	.10 [−.07 .27]
Waller, 2001*	FF	2282	Int. w2	.29 [−.06 .64]
RE Model				**.26 [.14 .37]**
Precision Interval				**[−.07 .59]**

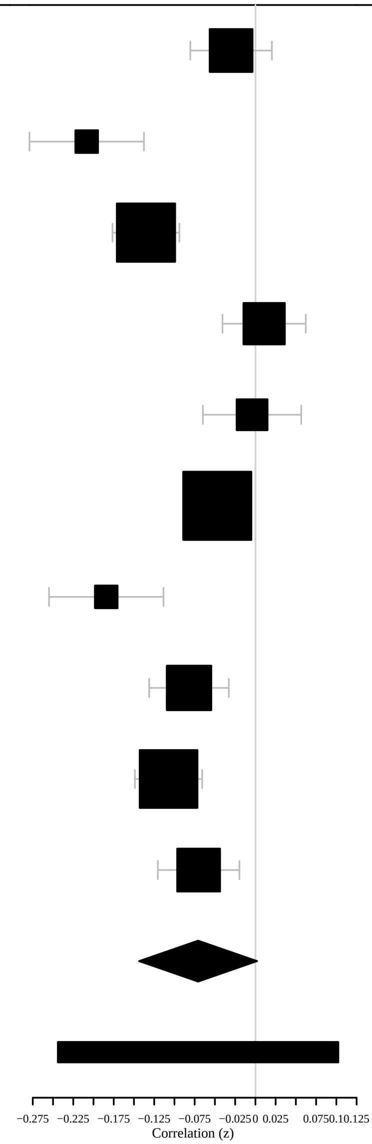


```
#dev.off()
```

12.3 Continuous Income on Symptoms

```
#png("plot-inconsymp.png",width=7.5,height=3,units="in",res=dpi)
c_forestplot(modellist=list(m.INCbySymp),
             tlist=NA,
             para="r",
             transfexp = FALSE,
             #title="",
             xlab="Correlation (z)",
             transf=transf.ztor,
             clip=c(-1,.25))
```

Paper	Cohort	n	Outcome	r [95% CI]
Panel Study of Income Dynamics, 2020*	PSID.CDS2	1455	Dep.	−.03 [−.08 .02]
Panel Study of Income Dynamics, 2020*	PSID.CDS2014	1045	Dep.	−.21 [−.28 −.14]
Zhang, 2012	PHDCN	1517	Ext.	−.14 [−.18 −.09]
Cohen & Hesselbart, 1993*	CIC	771	Ext.	.01 [−.04 .06]
Waller, 2001*	FF	1589	Ext.	−.00 [−.06 .06]
Waller, 2001*	FF	2257	Ext. w2	−.05 [−.08 −.01]
Xue et al., 2005	PHDCN	2805	Int.	−.18 [−.25 −.11]
Zhang, 2012	PHDCN	1517	Int.	−.08 [−.13 −.03]
Cohen & Hesselbart, 1993*	CIC	771	Int.	−.11 [−.15 −.07]
Waller, 2001*	FF	2230	Int. w2	−.07 [−.12 −.02]
RE Model				**−.07 [−.14 .00]**
Precision Interval				**[−.24 .10]**



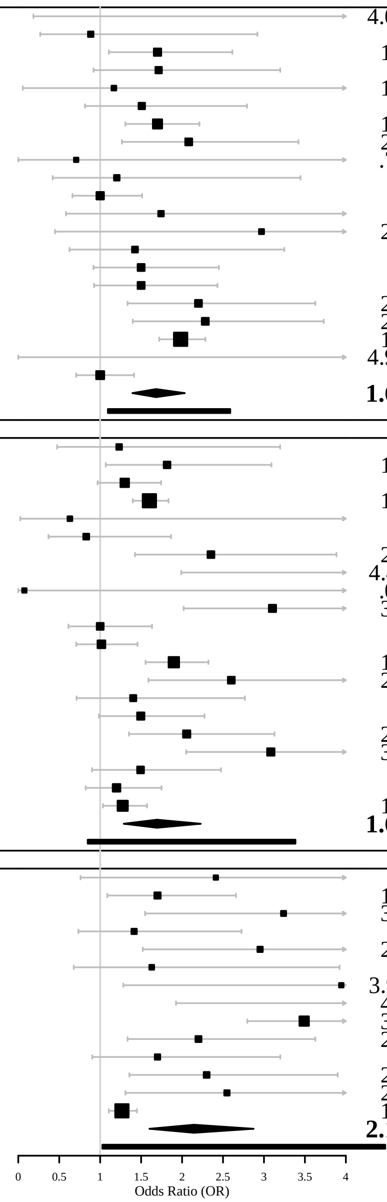
```
#dev.off()
```

12.4 Dichotomous SES on disorder.

- m.PEbyDis
- m.PVbyDis
- m.PAbyDis

```
#png("plot-dSESonDis.png",width=7.5,height=9.5,units="in",res=dpi)
c_forestplot(modellist=list(m.PEbyDis,m.PVbyDis,m.PAbyDis),
             tlist=list("Parent Education","Poverty","Public Assistance"),
             para="OR",
             transfexp = TRUE,
             xlab="Odds Ratio (OR)",
             zero=1,
             clip=c(-1,4))
```

Paper	Cohort	n	Outcome	OR [95% CI]
Parent Education				
Costello et al., 1996*	GSM	1420	ADHD	4.02 [.18 >50.00]
Lahey et al., 1996*	MECA	984	ADHD	.88 [.27 2.92]
Kessler et al., 2014	NCSA	6483	ADHD	1.70 [1.11 2.61]
Cohen & Hesselbart, 1993*	CIC	776	ADHD	1.71 [.92 3.20]
Costello et al., 1996*	GSM	1420	Anx.	1.17 [.05 24.88]
Lahey et al., 1996*	MECA	984	Anx.	1.51 [.81 2.79]
McLaughlin et al., 2012	NCSA	6483	Anx.	1.70 [1.31 2.21]
Cohen & Hesselbart, 1993*	CIC	776	Anx.	2.08 [1.27 3.42]
Costello et al., 1996*	GSM	1420	Dep.	.71 [.00 >50.00]
Lahey et al., 1996*	MECA	984	Dep.	1.20 [.42 3.45]
McLaughlin et al., 2012	NCSA	6483	Dep.	1.00 [.66 1.51]
Cohen & Hesselbart, 1993*	CIC	776	Dep.	1.74 [.58 5.21]
Costello et al., 1996*	GSM	1420	DBD	2.97 [.45 19.66]
Lahey et al., 1996*	MECA	984	DBD	1.43 [.63 3.25]
McLaughlin et al., 2012	NCSA	6483	DBD	1.50 [.92 2.45]
Loeber et al., 1998	PYS.y	503	DBD	1.50 [.93 2.43]
Loeber et al., 1998	PYS.o	506	DBD	2.20 [1.33 3.63]
Cohen & Hesselbart, 1993*	CIC	776	DBD	2.28 [1.40 3.73]
Xue et al., 2005	PHDCN	2805	Int.	1.98 [1.72 2.28]
Costello et al., 1996*	GSM	1420	PTSD	4.96 [.00 >50.00]
McLaughlin et al., 2013	NCSA	6483	PTSD	1.00 [.71 1.41]
RE Model				**1.68 [1.39 2.03]**
Precision Interval				**[1.09 2.59]**
Poverty				
Lahey et al., 1996*	MECA	970	ADHD	1.23 [.47 3.20]
Byrd, et. al., 2013	NHANES	3081	ADHD	1.82 [1.07 3.09]
Costello et al., 1996*	GSM	1420	ADHD	1.30 [.97 1.74]
Cohen & Hesselbart, 1993*	CIC	776	ADHD	1.60 [1.40 1.83]
Lahey et al., 1996*	MECA	970	Anx.	.63 [.02 16.21]
McLaughlin et al., 2012	NCSA	6483	Anx.	.83 [.37 1.87]
Costello et al., 1996*	GSM	1420	Anx.	2.35 [1.42 3.89]
Cohen & Hesselbart, 1993*	CIC	776	Anx.	4.49 [1.99 10.16]
Lahey et al., 1996*	MECA	970	Dep.	.07 [.00 >50.00]
McLaughlin et al., 2012	NCSA	6483	Dep.	3.10 [2.02 4.77]
Merikangas et al., 2012	NHANES	4150	Dep.	1.00 [.61 1.63]
Costello et al., 1996*	GSM	1420	Dep.	1.02 [.71 1.46]
Cohen & Hesselbart, 1993*	CIC	776	Dep.	1.90 [1.55 2.32]
Lahey et al., 1996*	MECA	970	DBD	2.60 [1.59 4.26]
McLaughlin et al., 2012	NCSA	6483	DBD	1.40 [.71 2.77]
Braun et al., 2008	NHANES	3081	DBD	1.50 [.98 2.27]
Cohen & Hesselbart, 1993*	CIC	776	DBD	2.06 [1.35 3.13]
Costello et al., 1996*	GSM	1420	DBD	3.08 [2.05 4.64]
Slopen et al., 2010	PHDCN	2810	Ext.	1.49 [.90 2.48]
Slopen et al., 2010	PHDCN	2810	Int.	1.20 [.82 1.75]
Costello et al., 1996*	GSM	1420	PTSD	1.28 [1.03 1.57]
RE Model				**1.69 [1.29 2.23]**
Precision Interval				**[.85 3.38]**
Public Assistance				
Lahey et al., 1996*	MECA	290	ADHD	2.41 [.76 7.65]
Loeber et al., 1998	PYS.y	503	ADHD	1.70 [1.09 2.66]
Cohen & Hesselbart, 1993*	CIC	776	ADHD	3.24 [1.55 6.78]
Lahey et al., 1996*	MECA	290	Anx.	1.41 [.73 2.73]
Cohen & Hesselbart, 1993*	CIC	776	Anx.	2.95 [1.52 5.73]
Lahey et al., 1996*	MECA	290	Dep.	1.63 [.68 3.92]
Cohen & Hesselbart, 1993*	CIC	776	Dep.	3.94 [1.28 12.13]
Lahey et al., 1996*	MECA	290	DBD	4.06 [1.93 8.55]
Keenan et al., 2010	PGS	2393	DBD	3.49 [2.80 4.36]
Loeber et al., 1998	PYS.y	503	DBD	2.20 [1.33 3.63]
Loeber et al., 1998	PYS.m	508	DBD	1.70 [.90 3.20]
Loeber et al., 1998	PYS.o	506	DBD	2.30 [1.36 3.90]
Cohen & Hesselbart, 1993*	CIC	776	DBD	2.55 [1.31 4.97]
Xue et al., 2005	PHDCN	2805	Int.	1.27 [1.11 1.45]
RE Model				**2.15 [1.60 2.87]**
Precision Interval				**[1.03 4.48]**

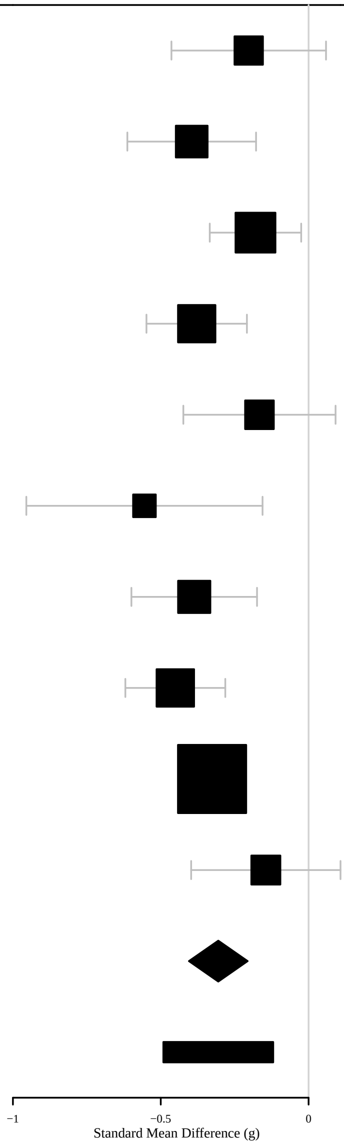


```
#dev.off()
```

12.5 SMD in Income with Disorder

```
#png("plot-incondis.svg",width=7.5,height=3,units="in",res=dpi)
c_forestplot(modellist=list(m.INCbyDis),
             tlist=NA,
             para="g",
             transfexp = FALSE,
             #title="Figure 4: SMD in income with disorder",
             xlab="Standard Mean Difference (g)",
             clip=c(-1,.25))
```

Paper	Cohort	n	Outcome	g [95% CI]
Lahey et al., 1996*	MECA	970	ADHD	−.20 [−.46 .06]
Cohen & Hesselbart, 1993*	CIC	771	ADHD	−.40 [−.61 −.18]
Lahey et al., 1996*	MECA	970	Anx.	−.18 [−.33 −.02]
Cohen & Hesselbart, 1993*	CIC	771	Anx.	−.38 [−.55 −.21]
Lahey et al., 1996*	MECA	970	Dep.	−.17 [−.42 .09]
Cohen & Hesselbart, 1993*	CIC	771	Dep.	−.56 [−.95 −.16]
Lahey et al., 1996*	MECA	970	DBD	−.39 [−.60 −.17]
Cohen & Hesselbart, 1993*	CIC	771	DBD	−.45 [−.62 −.28]
Xue et al., 2005	PHDCN	2805	Int.	−.33 [−.40 −.25]
McLaughlin et al., 2013	NCSA	6483	PTSD	−.14 [−.40 .11]
RE Model				**−.31 [−.40 −.21]**
Precision Interval				**[−.49 −.12]**



```
#dev.off()
```

12.6 Omnibus Plot

Here we have an additonal complication of needing our IVs displayed, and needing to split the figure between 3 pages, which means a different function.

12.6.1 Plotting Function

```
get_rma_data2<-function(rmamodel) {
  efids<-as.numeric(as.character(rmamodel$mf.r.f[[1]]$efid)) #Get the id numbers of the effects included in the specidied model, supposedl
  wi <- 1/sqrt(rmamodel$vi) #get a vector of weights
  psize<-wi/sum(wi,na.rm=TRUE) #calculate point size:
  psize<-(psize - min(psize, na.rm = TRUE))/(max(psize,na.rm = TRUE) - min(psize, na.rm = TRUE))
  psize <- (psize * 1) + 0.5
  #build a data frame for this model with all the stuff we want to display:
  df<-with(rmamodel,data.frame(SES="",
                              Paper=as.character(esdf[efids,"cite"]), #name of paper
                              Cohort=as.character(esdf[efids,"study.ID"]), #name of Cohort
                              n=as.character(esdf[efids,"n"]), #effect n
                              DV=esdf[efids,"DVshort"], #dependent variable
                              mean=yi, #effect
                              lower=yi-1.96*sqrt(vi), #lower CI
                              upper=yi+1.96*sqrt(vi), #upper CI
                              sum=FALSE, #these are not summary ariables.
                              psize=psize, #insert the point size
                              stringsAsFactors = FALSE)) #don't factorize
  esdf$IVshort<-factor(esdf$IVshort,levels=c("Hollingshead","Parent Ed.","Income","Assistance","Poverty","Subjective"))
  df<-df[order(esdf[efids,"IVshort"],esdf[efids,"Externalizing"],df$DV),] #order the df by dependent variable
  df$DV<-as.character(df$DV)  #convert DV back to a string.
  pred<-predict(rmamodel) #Get predictions from the model
  #Now we use the pred object to get our summary statistics:
  rbind(df,data.frame(SES=NA,
                      Paper=c("Summary","Precision Interval"),
                      Cohort=NA,
                      n=NA,
                      #pwhite=NA,
                      #mage=NA,
                      #IV=NA,
```

```
                      DV=NA,
                      mean=pred$pred,
                      lower=c(pred$ci.lb,pred$cr.lb),
                      upper=c(pred$ci.ub,pred$cr.ub),
                      sum=TRUE,
                      psize=c(1,.5),
                      stringsAsFactors = FALSE))
}

get_rmalist_data2<-function(mlist,tlist) {
  if(is.na(tlist)) {
    l<-lapply(mlist,get_rma_data2) #make sure the input is in the right format
  } else {
    titles<-lapply(tlist,function(x) {data.frame(SES=NA,
                                                 Paper=x, #generate subtitles
                        Cohort=NA,
                        n=NA,
                        #pwhite=NA,
                        #mage=NA,
                        DV=NA,
                        mean=NA,
                        lower=NA,
                        upper=NA,
                        sum=TRUE,
                        psize=FALSE)})
    models<-lapply(mlist,get_rma_data2) #generate data by iterating get_rma_data across the relevant models
    idx<-order(c(seq_along(titles),seq_along(models))) #order by title and then model output
    l<-(c(titles,models))[idx]
  }
  df<-do.call("rbind",l)
  df$Paper<-gsub('*',"ª",df$Paper,fixed=TRUE)
  df
}

c_forestplot2<-function(modellist,tlist=NA,para,transfexp=FALSE,plottedrows=NULL,summarylines=FALSE,...) {
  #Get Data
  plot.Data<-get_rmalist_data2(modellist,tlist)
```

```r
#Transform if necessary.
if(transfexp==TRUE) {
  plot.Data[,6:8]<-exp(plot.Data[,6:8])
}

#Format the Effect Summary line.
effectnums<-plot.Data[,6:8]
effectnums[plot.Data$Paper=="Precision Interval",1]<-NA
effectnums[!is.na(effectnums$mean),"mchar"]<-numform::f_num(na.omit(effectnums$mean),digits=2)
effectnums[!is.na(effectnums$lower),"lchar"]<-numform::f_num(na.omit(effectnums$lower),digits=2,p="[")
effectnums[!is.na(effectnums$upper),"uchar"]<-numform::f_num(na.omit(effectnums$upper),digits=2,s="]")
effectnums[effectnums$lower < -50 & !is.na(effectnums$lower),"lchar"]<-"[<-50.00"
effectnums[effectnums$upper > 50 & !is.na(effectnums$upper),"uchar"]<-">50.00]"
effectnums[is.na(effectnums)]<-""
plot.Data$paratext<-with(effectnums,paste(mchar,lchar,uchar,sep=" "))

#Add a header row
headers<-data.frame(SES="SES",
                    Paper="Paper",
                      Cohort="Cohort",
                      n="n",
                      #mage="Age",
                      #pwhite="White",
                      DV="Outcome",
                      mean=NA,
                      lower=NA,
                      upper=NA,
                      sum=TRUE,
                      psize=NA,
                      paratext=paste("g","[95% CI]",sep=" "), # always "g"
                      stringsAsFactors = FALSE)

if(is.null(plottedrows)) {
  plot.Data<-rbind(headers,plot.Data)
} else {
  plot.Data<-rbind(headers,plot.Data[plottedrows,])
}
```

```r
  #Build a vector of our point shapes
  sumfuncvector<-c(fpDrawBarCI,fpDrawBarCI)
  for (i in 1:dim(plot.Data)[1]) {
    if(plot.Data[i,"Paper"]=="Precision Interval") {
           sumfuncvector[[i]]<-fpDrawBarCI
         } else {
           sumfuncvector[[i]]<-fpDrawSummaryCI
         }
  }

  #Build a list for where we want our lines.
  hlineindices<-c(1,2) #above and below first line.
  if(summarylines) { #line below the last line and below the 3rd to last line.
    hlineindices<-c(hlineindices,dim(plot.Data)[1]-1,dim(plot.Data)[1]+1)
  }
  hlines<-as.list(rep(TRUE,length(hlineindices)))
  names(hlines)<-as.character(hlineindices)
  hlines
  forestplot(plot.Data[,c(1:5,11)],
             mean=plot.Data$mean,
             lower=plot.Data$lower,
             fn.ci_sum=sumfuncvector,
             upper=plot.Data$upper,
             is.summary=plot.Data$sum,
             align=c("l","l","c","l","l","r"),
             hrzl_lines = hlines,
             graph.pos=6,
             vertices=TRUE,
             colgap=unit(3,"mm"),
             boxsize=plot.Data$psize*.5,
             txt_gp=fpTxtGp(label=gpar(fontfamily="sans",fontsize="9"),
                            xlab=gpar(fontfamily="sans",cex="1"),
                            ticks=gpar(fontfamily="sans",cex="1")),
             graphwidth=unit(10,"cm"),
             mar=unit(rep(0,times=4),"mm"),
             ...) # feed any remaining args to the forestplot function
}
```

12.6.2 Call

See figure 2 in paper for output: SES labels and shading, as well as interpretaive axis labels, were added in a vector graphics program.

```
svg("plot-kitchen1.svg",width=10,height=7.25,bg=NA)
c_forestplot2(modellist=list(m.combined),
             tlist=NA,
             para="gcor",
             transfexp = FALSE,
             #title="Figure 4: SMD in income with disorder",
             xlab="Standard Mean Difference (g)",
             clip=c(-.5,1),
             plottedrows = 1:40,
             )
dev.off()
```

```
## pdf
##   2
```

```
svg("plot-kitchen2.svg",width=10,height=7.25,bg=NA)
c_forestplot2(modellist=list(m.combined),
             tlist=NA,
             para="gcor",
             transfexp = FALSE,
             #title="Figure 4: SMD in income with disorder",
             xlab="Standard Mean Difference (g)",
             clip=c(-.5,1),
             plottedrows = 41:86,
             xticks=c(-.5,0,.5,1)
             #summarylines=TRUE
             )
dev.off()
```

```
## pdf
##   2
```

```
svg("plot-kitchen3.svg",width=10,height=7.25,bg=NA)
c_forestplot2(modellist=list(m.combined),
             tlist=NA,
             para="gcor",
             transfexp = FALSE,
```

```
              #title="Figure 4: SMD in income with disorder",
              xlab="Standard Mean Difference (g)",
              clip=c(-.5,1),
              plottedrows = 87:122,
              summarylines=TRUE
              )
dev.off()
```

```
## pdf
##   2
```

12.7 Moderation Plot

Now we are plotting predictions generated by our final model. See figure 3 in the paper for output.

12.7.1 Plotting Function

```
finalpredict<-as.data.frame(predict(m.combined.intext.IV))
#finalpredict<-as.data.frame(predict(m.ml.combined.intext.IVint))
finalpredict$IV<-esdf$IV
finalpredict$Externalizing<-esdf$Externalizing

uniquepredict<-as.data.frame(finalpredict %>% group_by_all %>% count)

modforesttabledat<-uniquepredict[order(uniquepredict$IV,uniquepredict$Externalizing),c(8,7,9,1,2,3,4,5,6)]
modforesttable<-data.frame(IV=modforesttabledat$IV,
                            Externalizing=modforesttabledat$Externalizing,
                            k=modforesttabledat$n,
                            mean=modforesttabledat$pred,
                            lower=modforesttabledat$ci.lb,
                            upper=modforesttabledat$ci.ub)

modforesttable$Externalizing<-factor(modforesttable$Externalizing,labels=c("Internalizing","Externalizing"))

forestplotmods<-function(table,plottedrows=NULL,...) {
  #Get Data
  plot.Data<-table

  #Format the Effect Summary line.
```

```r
effectnums<-plot.Data[,4:6]
effectnums[!is.na(effectnums$mean),"mchar"]<-numform::f_num(na.omit(effectnums$mean),digits=2)
effectnums[!is.na(effectnums$lower),"lchar"]<-numform::f_num(na.omit(effectnums$lower),digits=2,p="[")
effectnums[!is.na(effectnums$upper),"uchar"]<-numform::f_num(na.omit(effectnums$upper),digits=2,s="]")
effectnums[effectnums$lower < -50 & !is.na(effectnums$lower),"lchar"]<-"[<-50.00"
effectnums[effectnums$upper > 50 & !is.na(effectnums$upper),"uchar"]<-">50.00]"
effectnums[is.na(effectnums)]<-""
plot.Data$paratext<-with(effectnums,paste(mchar,lchar,uchar,sep=" "))
#Add a header row
headers<-data.frame(IV="SES Measure",
                    Externalizing="Psychopathology Type",
                    k="k",
                    mean=NA,
                    lower=NA,
                    upper=NA,
                    paratext=paste("g","[95% CI]",sep=" "), # just g
                    stringsAsFactors = FALSE)

if(is.null(plottedrows)) {
  plot.Data<-rbind(headers,plot.Data)
} else {
  plot.Data<-rbind(headers,plot.Data[plottedrows,])
}

#Build a list for where we want our lines.
hlineindices<-c(1,2,dim(plot.Data)[1]+1) #above and below first line, after last line.
hlines<-as.list(rep(TRUE,length(hlineindices)))
names(hlines)<-as.character(hlineindices)

forestplot(plot.Data[,c(1:3,7)],
           mean=plot.Data$mean,
           lower=plot.Data$lower,
           fn.ci_norm=function(...) {fpDrawSummaryCI(col="black",...)},
           #fn.ci_sum = sumfuncvector,
           upper=plot.Data$upper,
           is.summary=c(TRUE,rep(FALSE,24)),
           align=c("l","l","r","r"),
           hrzl_lines = hlines,
```

```
             graph.pos=4,
             vertices=TRUE,
             colgap=unit(3,"mm"),
             boxsize=.5,
             txt_gp=fpTxtGp(label=gpar(fontfamily="sans",fontsize="10"),
                            xlab=gpar(fontfamily="sans",cex="1"),
                            ticks=gpar(fontfamily="sans",cex="1")),
             graphwidth=unit(8,"cm"),
             mar=unit(rep(0,times=4),"mm"),
             ...) # feed any remaining args to the forestplot function
}
```

12.7.2 Call

```
svg("plot-mods.svg",width=9.25,height=4,bg=NA)
forestplotmods(modforesttable,
             para="gcor",
             transfexp = FALSE,
             #title="Figure 4: SMD in income with disorder",
             xlab="Standard Mean Difference (g)",
             clip=c(-.1,.7)
             )
dev.off()
```

```
## pdf
##   2
```

13 Tables

13.1 Table functions

```
stats_rma.mv<-function(m,form,transf=NA) {
  predict<-predict(m,transf=transf)
  confint<-confint(m,transf=transf)
  df<-data.frame(estimate=predict$pred,
                 k=m$k,
                 ci.lb=predict$ci.lb,
                 ci.ub=predict$ci.ub,
```

```
                 pi.lb=predict$cr.lb,
                 pi.ub=predict$cr.ub,
                 pval=m$pval,
                 sigma2.between=m$sigma2[1],
                 sigma2.between.lb=confint[[1]]$random[1,2],
                 sigma2.between.ub=confint[[1]]$random[1,3],
                 sigma2.within=m$sigma2[2],
                 sigma2.within.lb=confint[[2]]$random[1,2],
                 sigma2.within.ub=confint[[2]]$random[1,3],
                 Q=m$QE,
                 Qp=m$QEp)
  df
}

ci_format<-function(est,low,upp,digitsnum=2) {
  gsub("NA ","",paste(numform::f_num(est,digits=digitsnum,zero=0),
        numform::f_num(low,digits=digitsnum,p=" [",zero=0),
        numform::f_num(upp,digits=digitsnum,p=",",s="]",zero=0),sep=""))

}

p_format<-function(p) {
 if(p<.001) {
   "<.001"
 }
  else {
   numform::f_num(p,digits=3)
  }
}

ps_format<-function(v) {
 sapply(v,p_format)
}

starPs<-function(p,s3=.001,s2=.01,s1=.05) {
  sapply(p,function(x) if(x<=s3) {
                          '***'
                        } else if(x<=s2) {
```

```
                        '**'
                      } else if(x<=s1) {
                        '*'
                      } else {""})
}
```

13.2 Bivariate Models (Table 1)

```
modelstatslist<-list(stats_rma.mv(m.combined,formula(gcor~I(1/n))),
                     stats_rma.mv(m.PEbySymp,formula(g~I(1/n))),
     stats_rma.mv(m.PVbySymp,formula(g~I(1/n))),
     stats_rma.mv(m.PAbySymp,formula(g~I(1/n))),
     stats_rma.mv(m.PEbyDis,formula(lOR~I(1/n)),transf=exp),
     stats_rma.mv(m.PVbyDis,formula(lOR~I(1/n)),transf=exp),
     stats_rma.mv(m.PAbyDis,formula(lOR~I(1/n)),transf=exp),
     stats_rma.mv(m.INCbySymp,formula(Zr~I(1/n)),transf=transf.ztor),
     stats_rma.mv(m.INCbyDis,formula(g~I(1/n))),
     stats_rma.mv(m.HollbySymp,formula(Zr~I(1/n))))

modelstatsdf<-as.data.frame(t(sapply(modelstatslist,rbind)))
modeltable<-with(modelstatsdf,data.frame(Model=c("Bivariate Model",
                                                 "Parent Ed. on Symptoms",
                   "Poverty on Symptoms",
                   "Public Assistance on Symptoms",
                   "Parent Ed. on Disorder",
                   "Poverty on Disorder",
                   "Public Assistance on Disorder",
                   "Income with Symptoms",
                   "Disorder on Income",
                   "Hollingshead on Symptoms"),
           Parameter=c(rep("g",4),
                   rep("lOR",3),
                   "r",
                   rep("g",2)),
           k=unlist(k),
           est=ci_format(estimate,ci.lb,ci.ub),
           p=ps_format(unlist(pval)),
           PI=ci_format("",pi.lb,pi.ub),
```

```
        sigma2.between=ci_format(sigma2.between,sigma2.between.lb,sigma2.between.ub,digitsnum=3),
        sigma2.within=ci_format(sigma2.within,sigma2.within.lb,sigma2.within.ub,digitsnum=3),
        Qest=numform::f_num(unlist(Q),digits=2,zero=0),
        Qpval=ps_format(unlist(Qp))
        )
        )

pander(modeltable)
```

Model	Parameter	k	est	p	PI	sigma2.between	sigma2.within	Qest	Qpval
Bivariate Model	g	120	.25 [.18,.32]	<.001	[-.05,.55]	.016 [.007,.040]	.007 [.004,.012]	497.17	<.001
Parent Ed. on Symptoms	g	10	.25 [.14,.35]	<.001	[-.01,.50]	.011 [0,.076]	.003 [0,.041]	23.48	.005
Poverty on Symptoms	g	10	.25 [.13,.38]	<.001	[-.07,.58]	.019 [0,.125]	.004 [0,.042]	34.22	<.001
Public Assistance on Symptoms	g	12	.26 [.14,.37]	<.001	[-.07,.59]	.014 [0,.090]	.011 [0,.066]	45.83	<.001
Parent Ed. on Disorder	lOR	21	1.68 [1.39,2.03]	<.001	[1.09,2.59]	.023 [0,.206]	.016 [0,.113]	25.98	.166
Poverty on Disorder	lOR	21	1.69 [1.29,2.23]	<.001	[.85,3.38]	.104 [.026,.553]	.002 [0,.055]	57.43	<.001
Public Assistance on Disorder	lOR	14	2.15 [1.60,2.87]	<.001	[1.03,4.48]	.118 [0,.532]	.001 [0,.293]	74.81	<.001
Income with Symptoms	r	10	-.07 [-.14,0]	.057	[-.24,.10]	.006 [.002,.042]	0 [0,.002]	54.42	<.001
Disorder on Income	g	10	-.31 [-.40,-.21]	<.001	[-.49,-.12]	.006 [0,.100]	0 [0,.017]	12.12	.207
Hollingshead on Symptoms	g	5	-.09 [-.22,.04]	.172	[-.34,.16]	.010 [0,.209]	.002 [0,.040]	31.51	<.001

```
write.csv(modeltable,file="modelstable.csv")
```

13.3 Moderation (Table 2)

```
modafunction<-function(rmamod) {
  summ<-summary(rmamod)
```

```
  return(c(numform::f_num(summ$QM,digits=2),
           summ$m,
           p_format(summ$QMp),
           starPs(summ$QMp)))
}
modmodels<-list(m.combined.intext.IV)
modmodelslabel<-c("Multiple Moderation")
modtablea<-data.frame(t(sapply(lapply(modmodels,modafunction),cbind)),row.names=modmodelslabel)
colnames(modtablea)<-c("QM","df","p","star")

modtableb<-rbind(sapply(summary(m.combined.intext.IV)[2:7],cbind))
row.names(modtableb)<-c(row.names(summary(m.combined.intext.IV)$b))
modtableb<-as.data.frame(modtableb)
modtableb$stars<-starPs(modtableb$pval)
modtableb$dash<-"-"

pander(modtableb[,c(1,7,2,3,4,5,8,6)],"modtableB.csv")
```

Table 44: modtableB.csv

	beta	stars	se	zval	pval	ci.lb	dash	ci.ub
intrcpt	0.16	***	0.045	3.7	0.00026	0.076	â€“	0.25
IVshortHollingshead	0.022		0.068	0.32	0.75	-0.11	â€“	0.16
IVshortParent Ed.	0.063		0.037	1.7	0.088	-0.0093	â€“	0.14
IVshortPoverty	0.058		0.035	1.6	0.1	-0.011	â€“	0.13
IVshortAssistance	0.13	***	0.038	3.4	0.00067	0.054	â€“	0.2
IVshortSubjective	0.049		0.067	0.72	0.47	-0.084	â€“	0.18
ExternalizingTRUE	0.056	*	0.026	2.2	0.03	0.0053	â€“	0.11

```
write.csv(modtableb[,c(1,7,2,3,4,5,8,6)],"modtableB.csv")
```

14 Supplemental Analyses

14.1 Interaction Model

We interpreted a two-moderator model without interaction as the final model, but the model fit statistics were somewhat ambiguous. The interaction model is presented below:

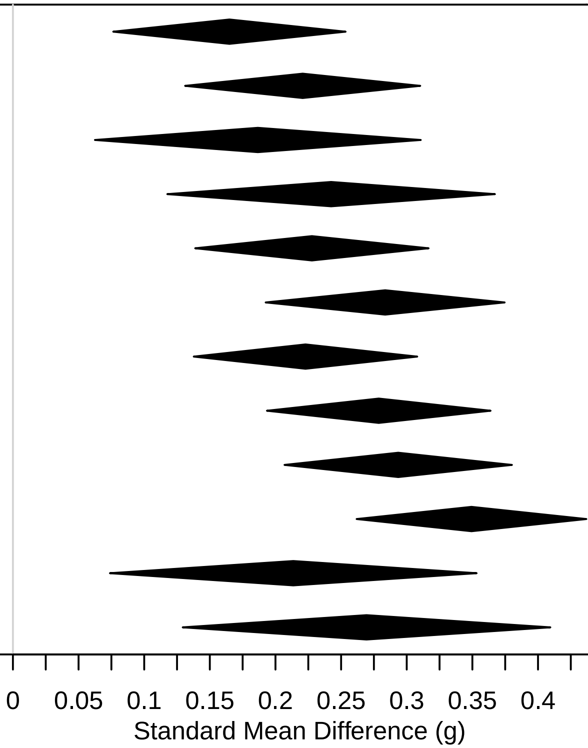
```r
m.combined.intext.IVint<-rma.mv(yi=gcor,
                        V=g.v,
                        mods= ~ IVshort*Externalizing,
                        random=~1 | study.ID/efid,
                        slab=paste(study.ID, efid,Externalizing,sep=" "),
                        data=esdf
                        )

summary(m.combined.intext.IVint)
```

```
##
## Multivariate Meta-Analysis Model (k = 120; method: REML)
##
##    logLik  Deviance       AIC       BIC      AICc
##   43.7452  -87.4903  -59.4903  -21.9405  -54.9742
##
## Variance Components:
##
##              estim    sqrt  nlvls  fixed         factor
## sigma^2.1  0.0156  0.1247     16     no       study.ID
## sigma^2.2  0.0045  0.0669    120     no  study.ID/efid
##
## Test for Residual Heterogeneity:
## QE(df = 108) = 334.7176, p-val < .0001
##
## Test of Moderators (coefficient(s) 2:12):
## QM(df = 11) = 30.6764, p-val = 0.0012
##
## Model Results:
##
##                                         estimate      se     zval    pval
## intrcpt                                   0.1784  0.0464   3.8466  0.0001
## IVshortHollingshead                      -0.0167  0.0825  -0.2028  0.8393
## IVshortParent Ed.                         0.0836  0.0427   1.9597  0.0500
## IVshortPoverty                            0.0467  0.0427   1.0935  0.2742
## IVshortAssistance                         0.0548  0.0445   1.2317  0.2181
## IVshortSubjective                         0.0337  0.0705   0.4774  0.6331
## ExternalizingTRUE                         0.0072  0.0470   0.1538  0.8778
## IVshortHollingshead:ExternalizingTRUE     0.0959  0.0998   0.9613  0.3364
```

```
## IVshortParent Ed.:ExternalizingTRUE     -0.0458  0.0692  -0.6614  0.5083
## IVshortPoverty:ExternalizingTRUE         0.0422  0.0628   0.6727  0.5011
## IVshortAssistance:ExternalizingTRUE      0.1770  0.0687   2.5782  0.0099
## IVshortSubjective:ExternalizingTRUE      0.0664  0.0972   0.6830  0.4946
##                                          ci.lb   ci.ub
## intrcpt                                 0.0875  0.2694  ***
## IVshortHollingshead                    -0.1784  0.1449
## IVshortParent Ed.                      -0.0000  0.1672    .
## IVshortPoverty                         -0.0370  0.1304
## IVshortAssistance                      -0.0324  0.1419
## IVshortSubjective                      -0.1045  0.1718
## ExternalizingTRUE                      -0.0850  0.0994
## IVshortHollingshead:ExternalizingTRUE  -0.0997  0.2915
## IVshortParent Ed.:ExternalizingTRUE    -0.1814  0.0899
## IVshortPoverty:ExternalizingTRUE       -0.0808  0.1653
## IVshortAssistance:ExternalizingTRUE     0.0424  0.3115   **
## IVshortSubjective:ExternalizingTRUE    -0.1241  0.2569
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

A prediction plot can be generated using the same procedure as in the moderation plot above:

SES Measure	Psychopathology Type	k	g [95% CI]
Family Income	Internalizing	12	.16 [.08 .25]
Family Income	Externalizing	8	.22 [.13 .31]
Hollingshead	Internalizing	4	.19 [.06 .31]
Hollingshead	Externalizing	5	.24 [.12 .37]
Parental Ed	Internalizing	17	.23 [.14 .32]
Parental Ed	Externalizing	14	.28 [.19 .37]
Poverty Status (poverty line)	Internalizing	16	.22 [.14 .31]
Poverty Status (poverty line)	Externalizing	15	.28 [.19 .36]
Receipt of Public Assistance	Internalizing	13	.29 [.21 .38]
Receipt of Public Assistance	Externalizing	13	.35 [.26 .44]
Subjective SES	Internalizing	2	.21 [.07 .35]
Subjective SES	Externalizing	1	.27 [.13 .41]



Over-all, the pattern is that the association of externalizing with public assistance is especially strong, which is in line with our points in the discussion that public assistance is highly related to material hardship, and that hardship is especially likely to relate to externalizing problems.

14.2 Sensitivity analysis.

14.2.1 Further Covariance Sensitivity Tests

We performed sensitivity tests using an inputed correlation between effects. Here we'll compare a model using our covariance matrix with some more arbitrarily chosen values. For example, in the code: V=with(esdf,clubSandwich::impute_covariance_matrix(g.v,study.ID,.1)), the trailing '.1' represents an estimated correlation of .1 between effects from the same cohort.

```
m.combined.intext.IV
```

```
##
```

```
## Multivariate Meta-Analysis Model (k = 120; method: REML)
##
## Variance Components:
##
##              estim    sqrt  nlvls  fixed         factor
## sigma^2.1  0.0151  0.1228     16     no       study.ID
## sigma^2.2  0.0058  0.0761    120     no  study.ID/efid
##
## Test for Residual Heterogeneity:
## QE(df = 113) = 367.6400, p-val < .0001
##
## Test of Moderators (coefficient(s) 2:7):
## QM(df = 6) = 17.7472, p-val = 0.0069
##
## Model Results:
##
##                      estimate      se    zval    pval    ci.lb   ci.ub
## intrcpt                0.1649  0.0452  3.6518  0.0003   0.0764  0.2534  ***
## IVshortHollingshead    0.0217  0.0683  0.3171  0.7512  -0.1122  0.1556
## IVshortParent Ed.      0.0628  0.0368  1.7061  0.0880  -0.0093  0.1350    .
## IVshortPoverty         0.0579  0.0352  1.6461  0.0998  -0.0111  0.1269    .
## IVshortAssistance      0.1286  0.0378  3.4015  0.0007   0.0545  0.2027  ***
## IVshortSubjective      0.0486  0.0675  0.7209  0.4710  -0.0836  0.1809
## ExternalizingTRUE      0.0558  0.0258  2.1668  0.0302   0.0053  0.1063    *
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
rma.mv(yi=gcor,
      mods = ~IVshort + Externalizing,
       V=with(esdf,clubSandwich::impute_covariance_matrix(g.v,study.ID,.1)),

       random=~1 | study.ID/efid,
       slab=paste(study.ID, efid,sep=" "),
       data=esdf
       )
```

```
##
## Multivariate Meta-Analysis Model (k = 120; method: REML)
##
```

```
## Variance Components:
##
##              estim    sqrt  nlvls  fixed         factor
## sigma^2.1  0.0141  0.1188     16     no       study.ID
## sigma^2.2  0.0061  0.0782    120     no  study.ID/efid
##
## Test for Residual Heterogeneity:
## QE(df = 113) = 314.8110, p-val < .0001
##
## Test of Moderators (coefficient(s) 2:7):
## QM(df = 6) = 17.8333, p-val = 0.0067
##
## Model Results:
##
##                       estimate      se    zval    pval    ci.lb   ci.ub
## intrcpt                 0.1660  0.0446  3.7200  0.0002   0.0785  0.2534  ***
## IVshortHollingshead     0.0201  0.0673  0.2982  0.7655  -0.1118  0.1519
## IVshortParent Ed.       0.0596  0.0367  1.6257  0.1040  -0.0123  0.1316
## IVshortPoverty          0.0567  0.0350  1.6193  0.1054  -0.0119  0.1252
## IVshortAssistance       0.1275  0.0378  3.3740  0.0007   0.0534  0.2016  ***
## IVshortSubjective       0.0394  0.0713  0.5528  0.5804  -0.1004  0.1792
## ExternalizingTRUE       0.0566  0.0255  2.2198  0.0264   0.0066  0.1065    *
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
rma.mv(yi=gcor,
      mods = ~IVshort + Externalizing,
       V=with(esdf,clubSandwich::impute_covariance_matrix(g.v,study.ID,.23)),

       random=~1 | study.ID/efid,
       slab=paste(study.ID, efid,sep=" "),
       data=esdf
       )
```

```
##
## Multivariate Meta-Analysis Model (k = 120; method: REML)
##
## Variance Components:
##
```

```
##              estim    sqrt  nlvls  fixed        factor
## sigma^2.1  0.0133  0.1153     16     no      study.ID
## sigma^2.2  0.0066  0.0811    120     no  study.ID/efid
##
## Test for Residual Heterogeneity:
## QE(df = 113) = 321.0608, p-val < .0001
##
## Test of Moderators (coefficient(s) 2:7):
## QM(df = 6) = 18.2001, p-val = 0.0058
##
## Model Results:
##
##                       estimate      se    zval    pval    ci.lb   ci.ub
## intrcpt                 0.1677  0.0442  3.7967  0.0001   0.0811  0.2543  ***
## IVshortHollingshead     0.0184  0.0661  0.2782  0.7808  -0.1111  0.1479
## IVshortParent Ed.       0.0559  0.0365  1.5328  0.1253  -0.0156  0.1273
## IVshortPoverty          0.0553  0.0347  1.5922  0.1113  -0.0128  0.1233
## IVshortAssistance       0.1272  0.0377  3.3708  0.0007   0.0532  0.2011  ***
## IVshortSubjective       0.0291  0.0754  0.3854  0.6999  -0.1188  0.1769
## ExternalizingTRUE       0.0571  0.0251  2.2749  0.0229   0.0079  0.1064    *
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
rma.mv(yi=gcor,
      mods = ~IVshort + Externalizing,
       V=with(esdf,clubSandwich::impute_covariance_matrix(g.v,study.ID,coresthigh)),

       random=~1 | study.ID/efid,
       slab=paste(study.ID, efid,sep=" "),
       data=esdf
       )
```

```
##
## Multivariate Meta-Analysis Model (k = 120; method: REML)
##
## Variance Components:
##
##              estim    sqrt  nlvls  fixed        factor
## sigma^2.1  0.0130  0.1142     16     no      study.ID
```

```
## sigma^2.2  0.0068  0.0823    120     no  study.ID/efid
##
## Test for Residual Heterogeneity:
## QE(df = 113) = 331.5183, p-val < .0001
##
## Test of Moderators (coefficient(s) 2:7):
## QM(df = 6) = 18.4022, p-val = 0.0053
##
## Model Results:
##
##                       estimate      se    zval    pval    ci.lb   ci.ub
## intrcpt                 0.1685  0.0441  3.8253  0.0001   0.0822  0.2549  ***
## IVshortHollingshead     0.0179  0.0656  0.2721  0.7855  -0.1108  0.1465
## IVshortParent Ed.       0.0544  0.0364  1.4960  0.1347  -0.0169  0.1256
## IVshortPoverty          0.0548  0.0346  1.5822  0.1136  -0.0131  0.1226
## IVshortAssistance       0.1273  0.0377  3.3761  0.0007   0.0534  0.2011  ***
## IVshortSubjective       0.0253  0.0769  0.3294  0.7418  -0.1254  0.1760
## ExternalizingTRUE       0.0573  0.0250  2.2940  0.0218   0.0083  0.1062    *
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
rma.mv(yi=gcor,
      mods = ~IVshort + Externalizing,
       V=with(esdf,clubSandwich::impute_covariance_matrix(g.v,study.ID,.3)),

       random=~1 | study.ID/efid,
       slab=paste(study.ID, efid,sep=" "),
       data=esdf
       )
```

```
##
## Multivariate Meta-Analysis Model (k = 120; method: REML)
##
## Variance Components:
##
##              estim    sqrt  nlvls  fixed         factor
## sigma^2.1  0.0130  0.1138     16     no       study.ID
## sigma^2.2  0.0068  0.0828    120     no  study.ID/efid
##
```

```
## Test for Residual Heterogeneity:
## QE(df = 113) = 335.9476, p-val < .0001
##
## Test of Moderators (coefficient(s) 2:7):
## QM(df = 6) = 18.4760, p-val = 0.0051
##
## Model Results:
##
##                         estimate      se    zval    pval    ci.lb   ci.ub
## intrcpt                   0.1688  0.0440  3.8347  0.0001   0.0825  0.2551  ***
## IVshortHollingshead       0.0177  0.0655  0.2703  0.7869  -0.1106  0.1460
## IVshortParent Ed.         0.0539  0.0363  1.4834  0.1380  -0.0173  0.1251
## IVshortPoverty            0.0546  0.0346  1.5788  0.1144  -0.0132  0.1224
## IVshortAssistance         0.1273  0.0377  3.3785  0.0007   0.0535  0.2012  ***
## IVshortSubjective         0.0241  0.0774  0.3116  0.7553  -0.1275  0.1757
## ExternalizingTRUE         0.0573  0.0249  2.3001  0.0214   0.0085  0.1062    *
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
rma.mv(yi=gcor,
      mods = ~IVshort + Externalizing,
       V=with(esdf,clubSandwich::impute_covariance_matrix(g.v,study.ID,.4)),

       random=~1 | study.ID/efid,
       slab=paste(study.ID, efid,sep=" "),
       data=esdf
       )
```

```
##
## Multivariate Meta-Analysis Model (k = 120; method: REML)
##
## Variance Components:
##
##             estim    sqrt  nlvls  fixed         factor
## sigma^2.1  0.0126  0.1121     16     no       study.ID
## sigma^2.2  0.0073  0.0854    120     no  study.ID/efid
##
## Test for Residual Heterogeneity:
## QE(df = 113) = 370.1072, p-val < .0001
```

```
##
## Test of Moderators (coefficient(s) 2:7):
## QM(df = 6) = 18.9328, p-val = 0.0043
##
## Model Results:
##
##                       estimate      se    zval    pval    ci.lb   ci.ub
## intrcpt                 0.1705  0.0439  3.8862  0.0001   0.0845  0.2565  ***
## IVshortHollingshead     0.0170  0.0647  0.2637  0.7920  -0.1097  0.1438
## IVshortParent Ed.       0.0509  0.0361  1.4083  0.1591  -0.0199  0.1217
## IVshortPoverty          0.0536  0.0344  1.5581  0.1192  -0.0138  0.1211
## IVshortAssistance       0.1278  0.0376  3.3965  0.0007   0.0541  0.2016  ***
## IVshortSubjective       0.0176  0.0799  0.2203  0.8257  -0.1390  0.1742
## ExternalizingTRUE       0.0575  0.0247  2.3313  0.0197   0.0092  0.1058    *
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
rma.mv(yi=gcor,
      mods = ~IVshort + Externalizing,
       V=with(esdf,clubSandwich::impute_covariance_matrix(g.v,study.ID,.5)),

       random=~1 | study.ID/efid,
       slab=paste(study.ID, efid,sep=" "),
       data=esdf
       )
```

```
##
## Multivariate Meta-Analysis Model (k = 120; method: REML)
##
## Variance Components:
##
##             estim    sqrt  nlvls  fixed        factor
## sigma^2.1  0.0122  0.1106     16     no      study.ID
## sigma^2.2  0.0078  0.0886    120     no  study.ID/efid
##
## Test for Residual Heterogeneity:
## QE(df = 113) = 423.9046, p-val < .0001
##
## Test of Moderators (coefficient(s) 2:7):
```

```
## QM(df = 6) = 19.4316, p-val = 0.0035
##
## Model Results:
##
##                      estimate      se    zval    pval    ci.lb   ci.ub
## intrcpt                0.1724  0.0438  3.9342  <.0001   0.0865  0.2582  ***
## IVshortHollingshead    0.0169  0.0639  0.2637  0.7920  -0.1084  0.1422
## IVshortParent Ed.      0.0476  0.0360  1.3219  0.1862  -0.0230  0.1182
## IVshortPoverty         0.0526  0.0343  1.5324  0.1254  -0.0147  0.1199
## IVshortAssistance      0.1287  0.0376  3.4184  0.0006   0.0549  0.2024  ***
## IVshortSubjective      0.0116  0.0824  0.1414  0.8876  -0.1498  0.1731
## ExternalizingTRUE      0.0575  0.0244  2.3549  0.0185   0.0096  0.1054    *
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
rma.mv(yi=gcor,
      mods = ~IVshort + Externalizing,
       V=with(esdf,clubSandwich::impute_covariance_matrix(g.v,study.ID,.6)),

       random=~1 | study.ID/efid,
       slab=paste(study.ID, efid,sep=" "),
       data=esdf
       )
```

```
##
## Multivariate Meta-Analysis Model (k = 120; method: REML)
##
## Variance Components:
##
##             estim    sqrt  nlvls  fixed         factor
## sigma^2.1  0.0119  0.1091     16     no       study.ID
## sigma^2.2  0.0085  0.0924    120     no  study.ID/efid
##
## Test for Residual Heterogeneity:
## QE(df = 113) = 509.3432, p-val < .0001
##
## Test of Moderators (coefficient(s) 2:7):
## QM(df = 6) = 19.9280, p-val = 0.0029
##
```

```
## Model Results:
##
##                        estimate      se    zval    pval    ci.lb   ci.ub
## intrcpt                  0.1743  0.0438  3.9772  <.0001   0.0884  0.2602  ***
## IVshortHollingshead      0.0172  0.0633  0.2721  0.7855  -0.1069  0.1414
## IVshortParent Ed.        0.0438  0.0360  1.2160  0.2240  -0.0268  0.1144
## IVshortPoverty           0.0515  0.0344  1.4963  0.1346  -0.0160  0.1189
## IVshortAssistance        0.1298  0.0378  3.4386  0.0006   0.0558  0.2038  ***
## IVshortSubjective        0.0061  0.0849  0.0718  0.9428  -0.1603  0.1725
## ExternalizingTRUE        0.0574  0.0242  2.3664  0.0180   0.0099  0.1049    *
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

As imputed covariance raises, the effect estimates do not change very much.

14.2.2 Beta conversion

What changes if we do not include beta weights converted in to r values via Peterson and Brown's formula?

```r
nonbetas<-esdf[is.na(esdf$beta),"efid"]
#Omnibus
rma.mv(yi=gcor,
       V=g.v,

       random=~1 | study.ID/efid,
       slab=paste(study.ID, efid,sep=" "),
       data=esdf[esdf$efid %in% nonbetas,]
       )
```

```
##
## Multivariate Meta-Analysis Model (k = 110; method: REML)
##
## Variance Components:
##
##             estim    sqrt  nlvls  fixed        factor
## sigma^2.1  0.0146  0.1208     15     no      study.ID
## sigma^2.2  0.0054  0.0734    110     no  study.ID/efid
##
## Test for Heterogeneity:
## Q(df = 109) = 413.0350, p-val < .0001
```

```
##
## Model Results:
##
## estimate      se    zval    pval   ci.lb   ci.ub
##   0.2614  0.0351  7.4481  <.0001  0.1926  0.3302  ***
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
rma.mv(yi=gcor,
       V=g.v,
       mods = ~ IVshort + Externalizing,

       random=~1 | study.ID/efid,
       slab=paste(study.ID, efid,sep=" "),
       data=esdf[esdf$efid %in% nonbetas,]
       )
```

```
##
## Multivariate Meta-Analysis Model (k = 110; method: REML)
##
## Variance Components:
##
##             estim    sqrt  nlvls  fixed         factor
## sigma^2.1  0.0123  0.1111     15     no       study.ID
## sigma^2.2  0.0029  0.0542    110     no  study.ID/efid
##
## Test for Residual Heterogeneity:
## QE(df = 103) = 258.5000, p-val < .0001
##
## Test of Moderators (coefficient(s) 2:7):
## QM(df = 6) = 28.6155, p-val < .0001
##
## Model Results:
##
##                       estimate      se    zval    pval    ci.lb   ci.ub
## intrcpt                 0.1599  0.0420  3.8080  0.0001   0.0776  0.2422  ***
## IVshortHollingshead     0.1116  0.0771  1.4476  0.1477  -0.0395  0.2627
## IVshortParent Ed.       0.0459  0.0362  1.2660  0.2055  -0.0251  0.1169
## IVshortPoverty          0.0712  0.0312  2.2829  0.0224   0.0101  0.1323    *
```

```
## IVshortAssistance      0.1831  0.0381  4.8076  <.0001   0.1084  0.2577  ***
## IVshortSubjective      0.0429  0.0567  0.7575  0.4488  -0.0682  0.1540
## ExternalizingTRUE      0.0444  0.0235  1.8915  0.0586  -0.0016  0.0904    .
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
rma.mv(yi=gcor,
       V=clubSandwich::impute_covariance_matrix(esdf[esdf$efid %in% nonbetas,]$g.v,esdf[esdf$efid %in% nonbetas,]$study.ID,corestlow),
       mods = ~ IVshort + Externalizing,

       random=~1 | study.ID/efid,
       slab=paste(study.ID, efid,sep=" "),
       data=esdf[esdf$efid %in% nonbetas,]
       )
```

```
##
## Multivariate Meta-Analysis Model (k = 110; method: REML)
##
## Variance Components:
##
##              estim    sqrt  nlvls  fixed         factor
## sigma^2.1  0.0114  0.1068     15     no       study.ID
## sigma^2.2  0.0034  0.0583    110     no  study.ID/efid
##
## Test for Residual Heterogeneity:
## QE(df = 103) = 206.0998, p-val < .0001
##
## Test of Moderators (coefficient(s) 2:7):
## QM(df = 6) = 28.0603, p-val < .0001
##
## Model Results:
##
##                      estimate      se    zval    pval    ci.lb   ci.ub
## intrcpt                0.1623  0.0415  3.9084  <.0001   0.0809  0.2438  ***
## IVshortHollingshead    0.1078  0.0756  1.4270  0.1536  -0.0403  0.2559
## IVshortParent Ed.      0.0440  0.0362  1.2153  0.2243  -0.0270  0.1150
## IVshortPoverty         0.0690  0.0313  2.2059  0.0274   0.0077  0.1303    *
## IVshortAssistance      0.1800  0.0383  4.7019  <.0001   0.1049  0.2550  ***
## IVshortSubjective      0.0333  0.0616  0.5407  0.5887  -0.0874  0.1540
```

```
## ExternalizingTRUE      0.0458  0.0235  1.9518  0.0510  -0.0002  0.0918    .
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Coefficients are substantially the same. Poverty becomes barely significant as a predictor and externalizing becomes marginal.

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