

Part3_Results

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2024-09-12

This file assumes that the code in `Part1_Harmonization_continuous.Rmd` and `Part2_Harmonization_ordinal.Rmd` have been run. These two files result in the rds files that will be read in within the current file. If those files have not been run yet, please run the files to prepare the relevant rds files.

Install and load packages, prepare data.

```
library(dplyr)
library(lavaan)
library(sirt)
library(mirt)
library(kableExtra)
library(here)
library(ggplot2)
# also install packages: haven, numDeriv

dat <- readRDS("rds/dat.rds")

est_partial <- readRDS("rds/est_partial.rds")
est_align <- readRDS("rds/est_align.rds")
est_partial_ord <- readRDS("rds/est_partial_ord.rds")
est_align_ord <- readRDS("rds/est_align_ord.rds")
est_align_ord_th <- readRDS("rds/est_align_ord_th.rds")
est_align_ord_lam <- readRDS("rds/est_align_ord_lam.rds")
fit_partial <- readRDS("rds/fit_partial.rds")
fit_align <- readRDS("rds/fit_align.rds")
mod_aligned <- readRDS("rds/mod_aligned.rds")

score_df_cont <- readRDS("rds/score_df_continuous.rds")
score_df_ord <- readRDS("rds/score_df_ord.rds")
df <- cbind(score_df_cont, score_df_ord[,c("approx_ord", "approx_ord_SE", "approx_ord_rel", "approx_ord_ev")])
head(df, 2)

##      stu_id sample sex dropout i1 i2 i3 i4 i5 mean_score partial_cont
## ELS1 101101    ELS   0       0  2  1  2  2  1        1.6     -1.114292
## ELS2 101102    ELS   0       0  4  3  4  4  4        3.8      1.658808
##      partial_SE approx_cont approx_SE partial_rel approx_rel partial_ev
## ELS1  0.278666   -1.131463  0.2781254   0.927941  0.9282002  0.07765475
## ELS2  0.278666    1.661305  0.2781254   0.927941  0.9282002  0.07765475
##      approx_ev approx_ord approx_ord_SE approx_ord_rel approx_ord_ev
## ELS1  0.07735375  -1.018915    0.2476258     0.9386815    0.05755857
## ELS2  0.07735375   1.312507    0.2987173     0.9107680    0.08126969
```

```
saveRDS(df, "rds/df.rds")
m_items <- paste0("i", 1:5)
```

Also source the following R file to repeat the analyses up to this point on the dataset without any NAs for later sensitivity analyses.

```
if (!all(file.exists("rds/score_df_noNAs.rds",
                     "rds/fit_partial_noNAs.rds",
                     "rds/fit_align_noNAs.rds",
                     "rds/est_align_ord_noNAs.rds")) {
  source("code/repeatAnalysesNoNAs.R")
} else {
  complete_cases <- complete.cases(dat[, m_items]) & dat$sample == "ELS" |
    complete.cases(dat[, m_items[-3]]) & dat$sample == "HSLS"
  d_noNAs <- dat[complete_cases, ]
  fit_partial_noNAs <- readRDS("rds/fit_partial_noNAs.rds")
  fit_align_noNAs <- readRDS("rds/fit_align_noNAs.rds")
  est_align_ord_noNAs <- readRDS("rds/est_align_ord_noNAs.rds")

  score_df_noNAs <- readRDS("rds/score_df_noNAs.rds")
}
```

```
## Iteration: 1, Log-Lik: -143161.234, Max-Change: 2.93816Iteration: 2, Log-Lik: -116756.822, Max-Change
## Iteration: 1, Log-Lik: -142906.991, Max-Change: 2.92118Iteration: 2, Log-Lik: -117479.479, Max-Change
```

Table 1: Models by approach and dataset

			Continuous		Ordinal	
	Mean	Score	Partial	Approximate	Partial	Approximate
N = 30,749	M_B1		M1	M2	-	M3
N = 29,202	M_B2		M4	M5	M6	M7

```
source('code/table_helper_functions.R')
```

Table 2: Loading estimates by approach and dataset

	Continuous				Ordinal			
	Partial (M1)		Approximate (M2)		Partial (M6)		Approximate (M3)	
	ELS	HSLS	ELS	HSLS	ELS	HSLS	ELS	HSLS
i1	0.74	0.86	0.74	0.75	1.60	1.73	3.37	3.92
i2	0.73	0.91	0.73	0.80	1.51	1.58	3.48	3.04
i3	0.83	NA	0.83	NA	2.05	NA	4.37	NA
i4	0.86	0.86	0.85	0.76	2.91	2.91	4.37	4.38
i5	0.82	0.82	0.84	0.72	2.40	2.40	4.34	3.88

Table 3: Intercept estimates by approach and dataset

Continuous	
Partial (M1)	Approximate (M2)

	ELS	HSLS	ELS	HSLS
i1	2.54	2.57	2.54	2.60
i2	2.36	2.30	2.36	2.32
i3	2.46	NA	2.46	NA
i4	2.65	2.65	2.62	2.69
i5	2.62	2.62	2.65	2.62

Table 6: Mean and SD of scores by approach and dataset

	N = 30,740	Continuous								Ordinal			
		Mean Score		Partial		Approximate		Partial		Approximate			
		M	SD	M	SD	M	SD	M	SD	M	SD		
M_B1		M1		M2		M3							
ELS	2.52	0.845	-0.003	1.051	-0.004	1.051	-	-	-	-0.001	0.952		
HSLS	2.938	0.661	0.469	0.763	0.501	0.869	-	-	-	0.619	0.908		
overall	2.779	0.764	0.29	0.912	0.31	0.973	-	-	-	0.384	0.973		
M_B1		M4		M5		M6		M7					
ELS	2.545	0.833	0	1.038	0	1.038	0.001	0.939	-0.001	0.957			
HSLS	2.938	0.661	0.45	0.767	0.477	0.869	0.022	0.784	0.574	0.904			
overall	2.797	0.751	0.289	0.9	0.306	0.96	0.015	0.843	0.368	0.964			

Table 4: Threshold estimates by approach and dataset

	Ordinal				
	Partial (M6)		Approximate (M3)		
	ELS	HSLS	ELS	HSLS	
	i1 t1	-2.41	-2.41	4.72	4.75
i1 t2	0.26	-0.71	3.49	2.85	
i1 t3	1.58	1.58	4.50	NA	
i2 t1	-1.74	-1.74	5.64	5.63	
i2 t2	0.45	-0.05	5.74	4.94	
i2 t3	1.90	1.90	-0.44	0.35	
i3 t1	-2.33	NA	-0.88	-0.93	
i3 t2	0.28	NA	-0.48	NA	
i3 t3	2.06	NA	0.29	1.24	
i4 t1	-4.01	-4.01	0.44	0.56	
i4 t2	-0.16	-1.68	-3.07	-5.61	
i4 t3	2.39	2.39	-4.18	-5.50	
i5 t1	-3.39	-3.39	-4.26	NA	
i5 t2	-0.23	-1.10	-3.56	-5.78	
i5 t3	1.92	2.32	-3.41	-5.78	

Table 5: Latent mean and variance estimates by approach and dataset

	Continuous				Ordinal			
	Partial (M1)		Approximate (M2)		Partial (M6)		Approximate (M3)	
	ELS	HSLS	ELS	HSLS	ELS	HSLS	ELS	HSLS
Latent mean	0	0.47	0	0.50	0	0.28	0	0.70
Latent variance	1	0.53	1	0.69	1	0.66	1	0.94

Table 7: Correlation of FS (N = 30,740)

Mean scores	Continuous			Ordinal	
	Partial	Approximate	Partial	Approximate	
	M_B1	M1	M2	-	M3
M_B1	1	0.992	0.993	-	0.989
M1	0.992	1	0.998	-	0.98
M2	0.993	0.998	1	-	0.986
-	-	-	-	-	-
M3	0.989	0.98	0.986	-	1

Table 8: Correlation of FS on dataset with no NAs (N = 29,202)

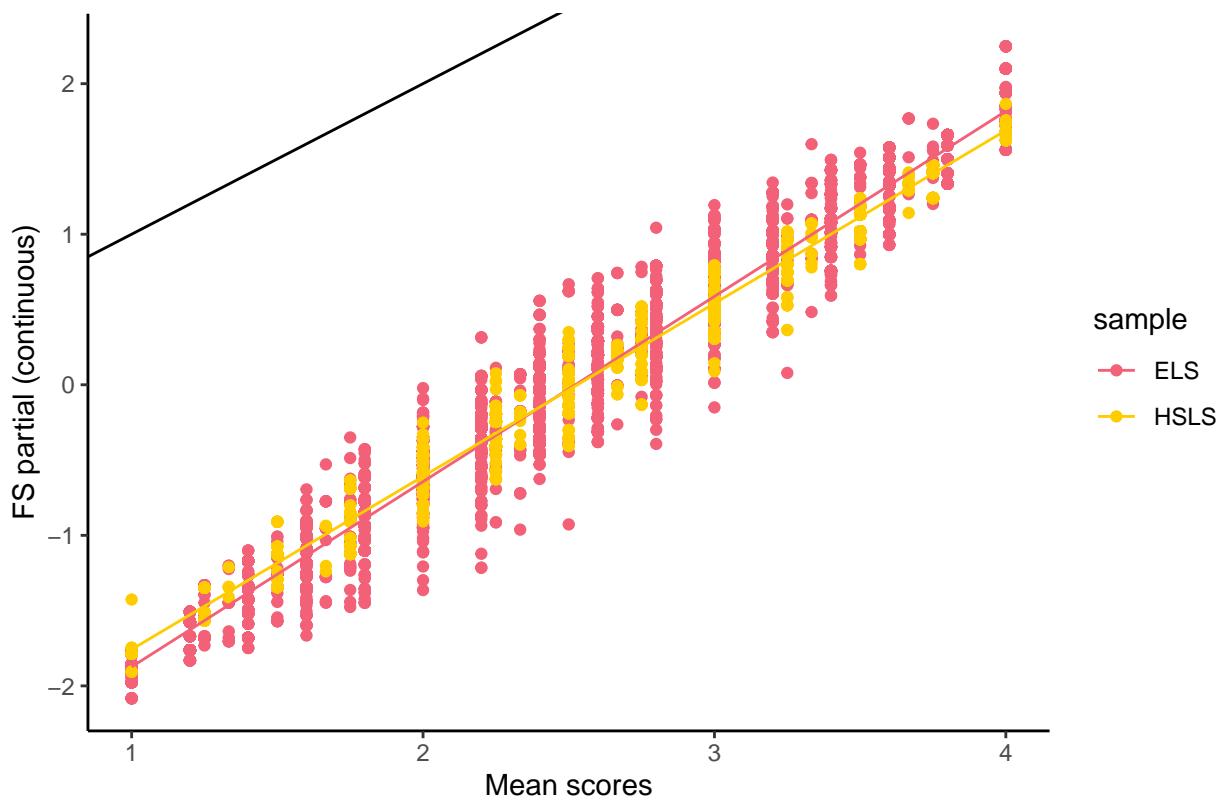
Mean scores	Continuous			Ordinal	
	Partial	Approximate	Partial	Approximate	
	M_B2	M4	M5	M6	M7
M_B2	1	0.992	0.993	0.965	0.991
M4	0.992	1	0.998	0.964	0.983
M5	0.993	0.998	1	0.966	0.988
M6	0.965	0.964	0.966	1	0.957
M7	0.991	0.983	0.988	0.957	1

Score distributions

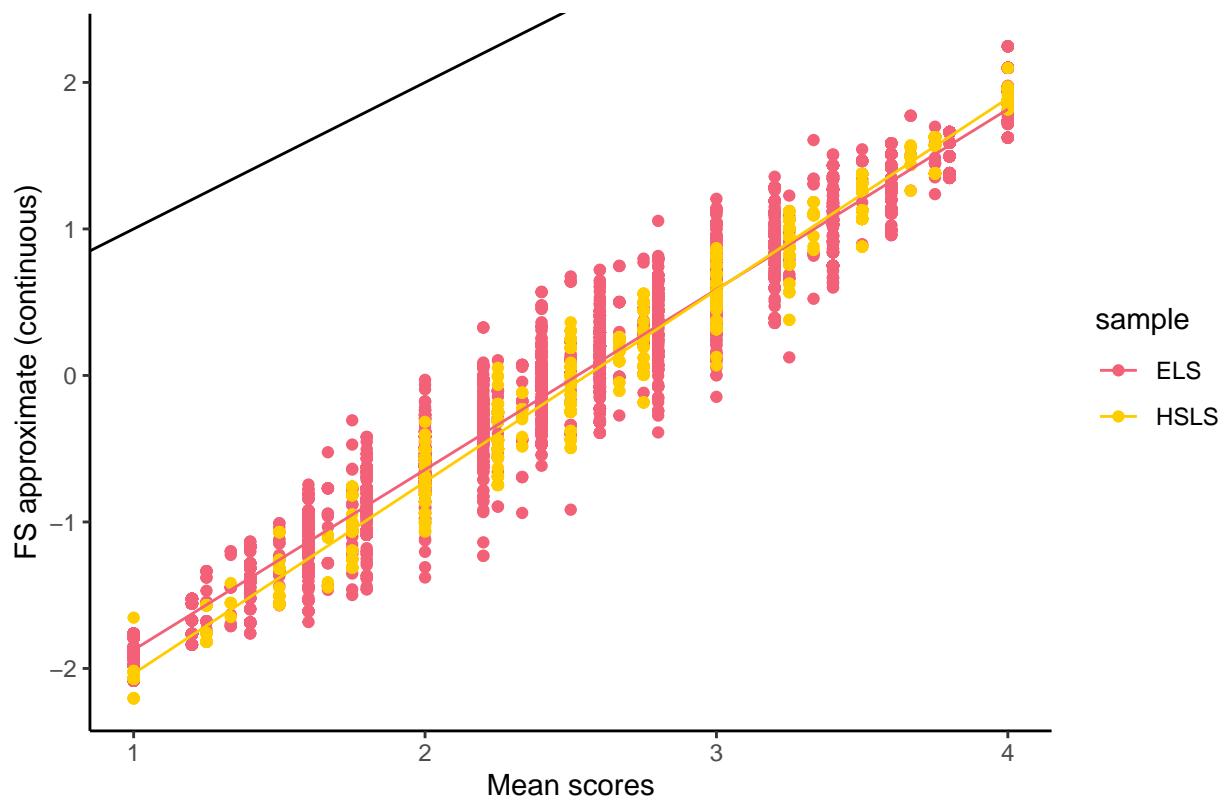
Score correlations

```
# compute matrix of correlations
cor_30749 <- cor(df[, c("mean_score", "partial_cont", "approx_cont", "approx_ord")], use = "complete.obs")
```

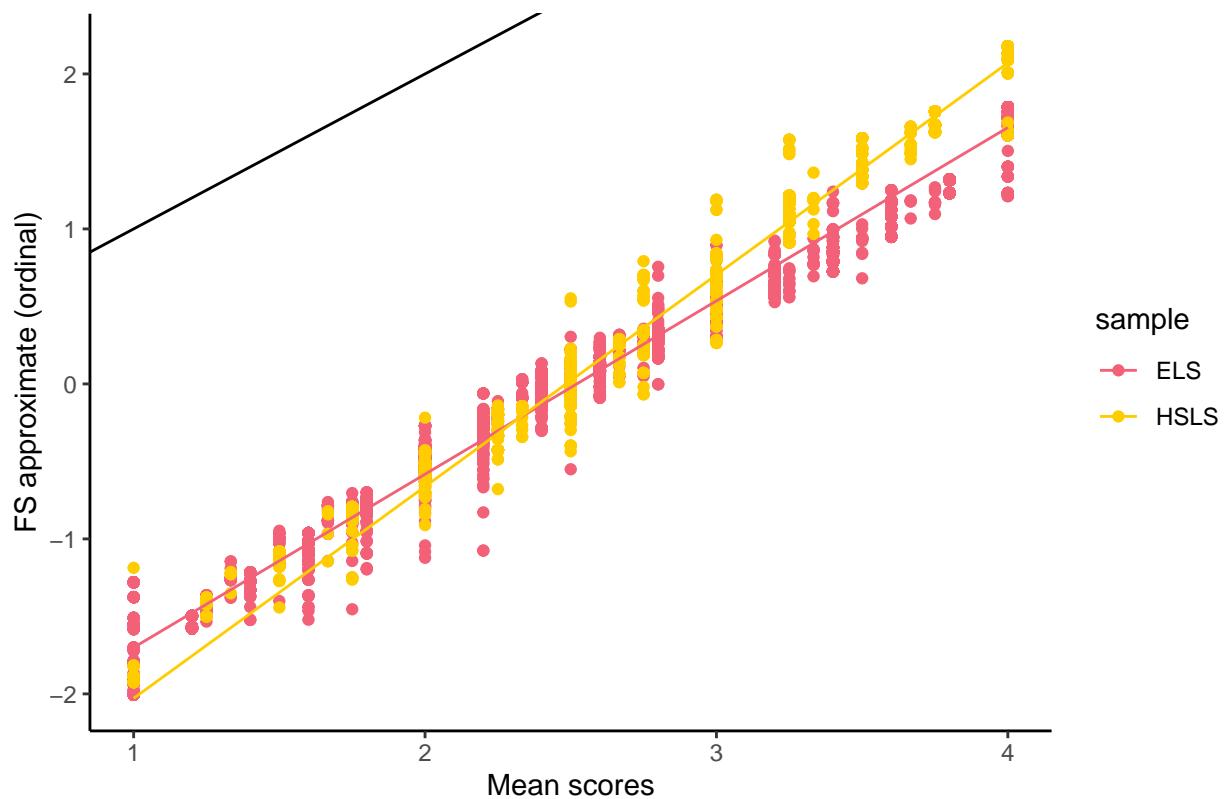
Correlation of mean scores and FS partial (cont.; M1)



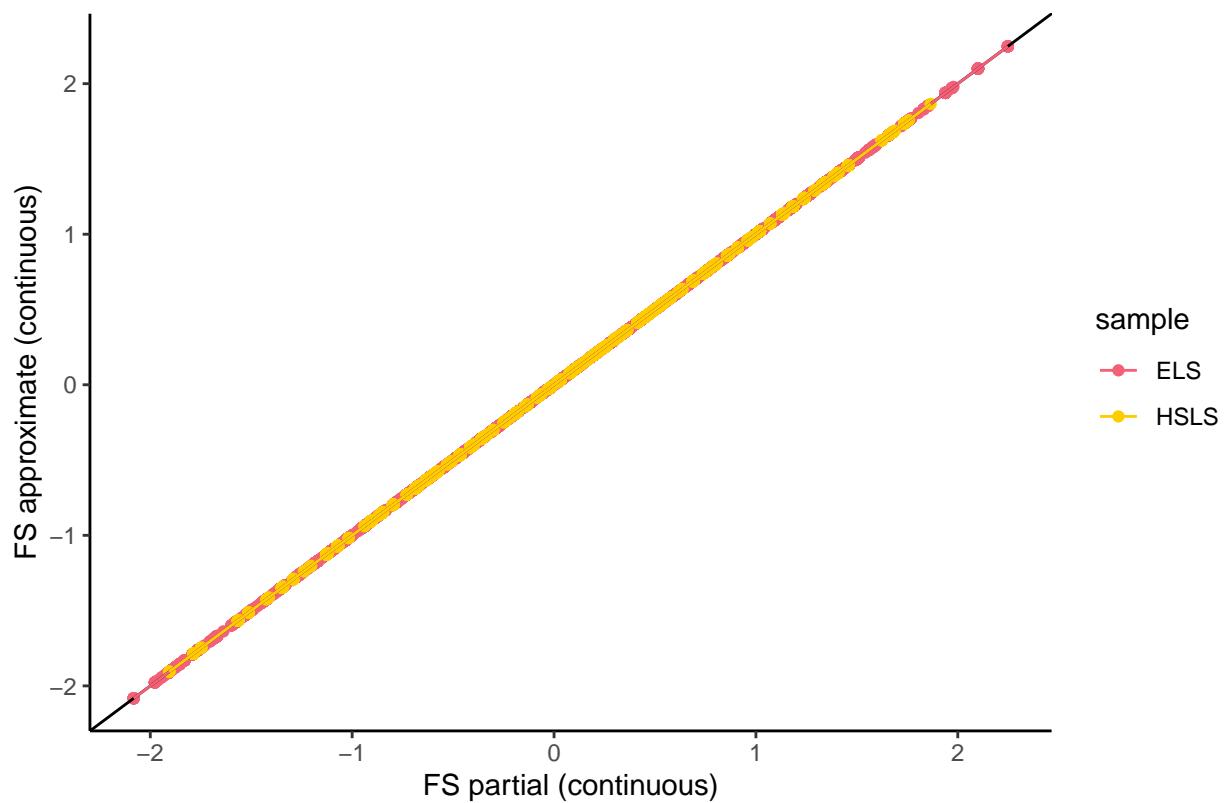
Correlation of mean scores and FS approximate (cont.; M2)



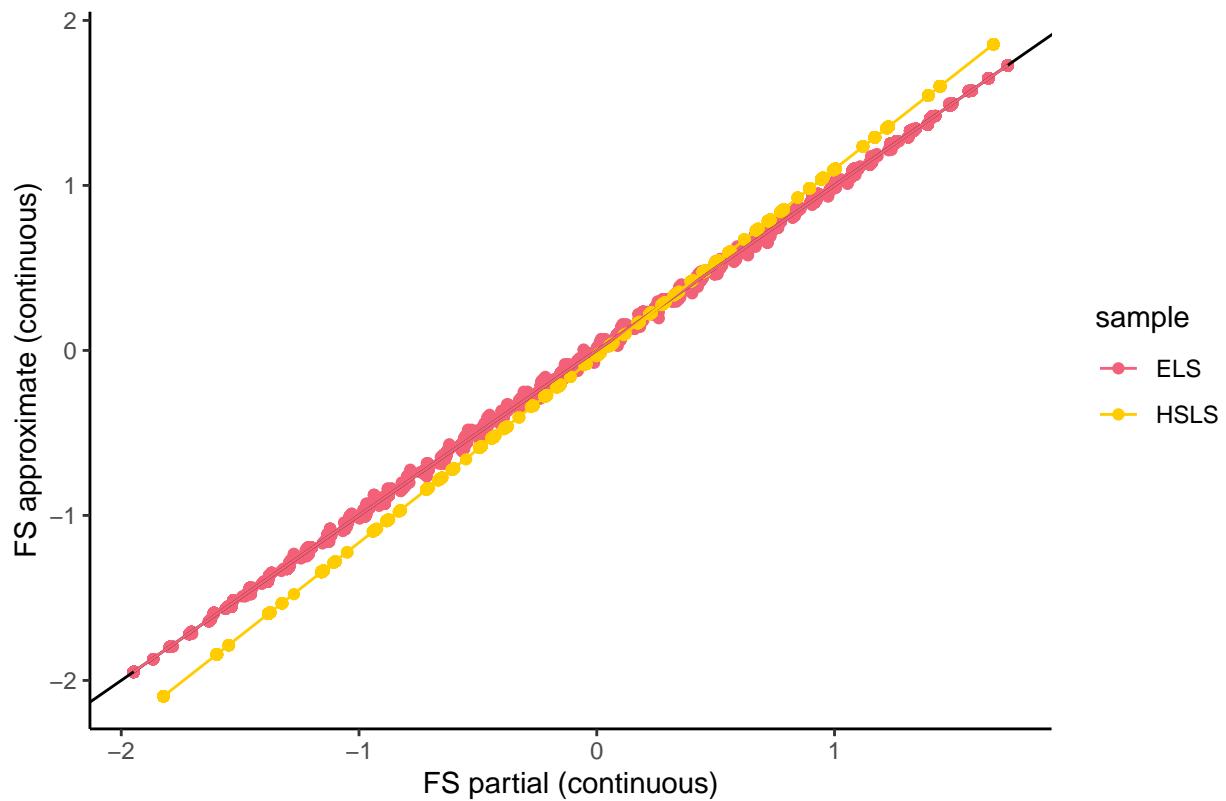
Correlation of mean scores and FS approximate (ordinal; M3)



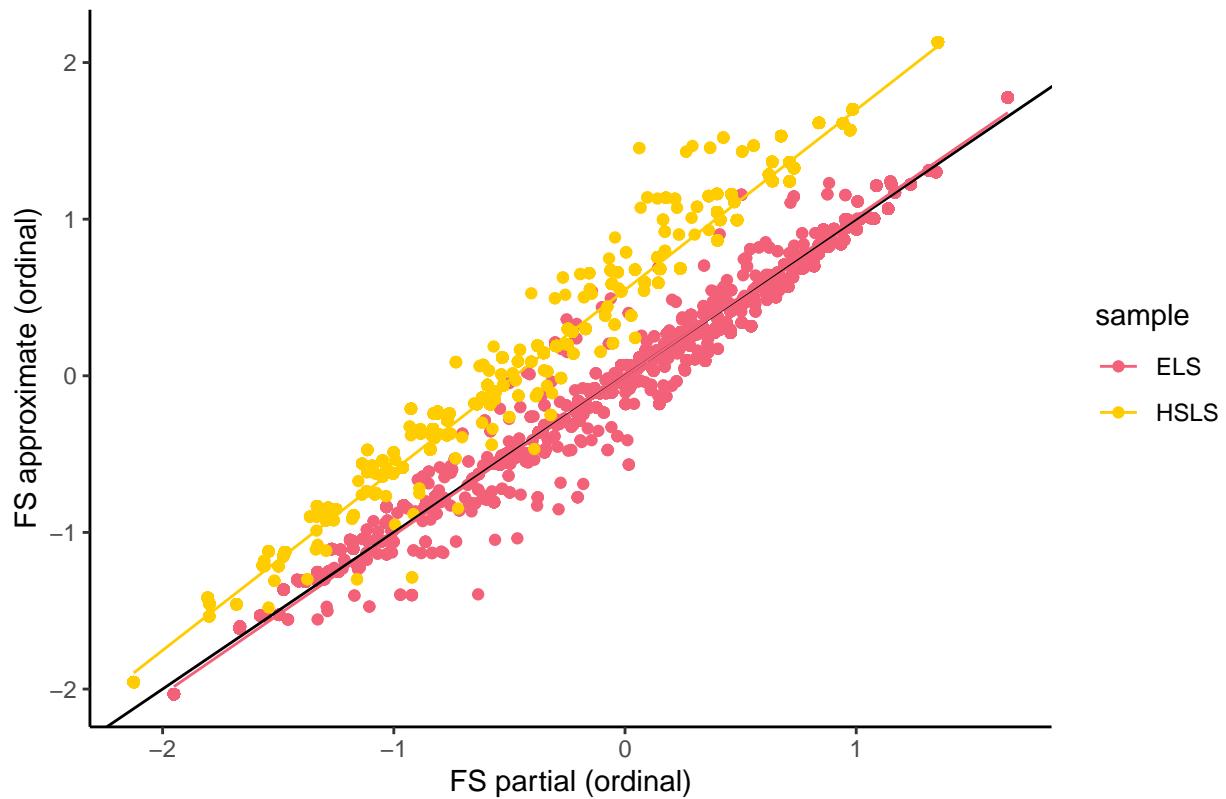
Correlation of FS: partial (cont.; M1) or approximate (cont.; M2)



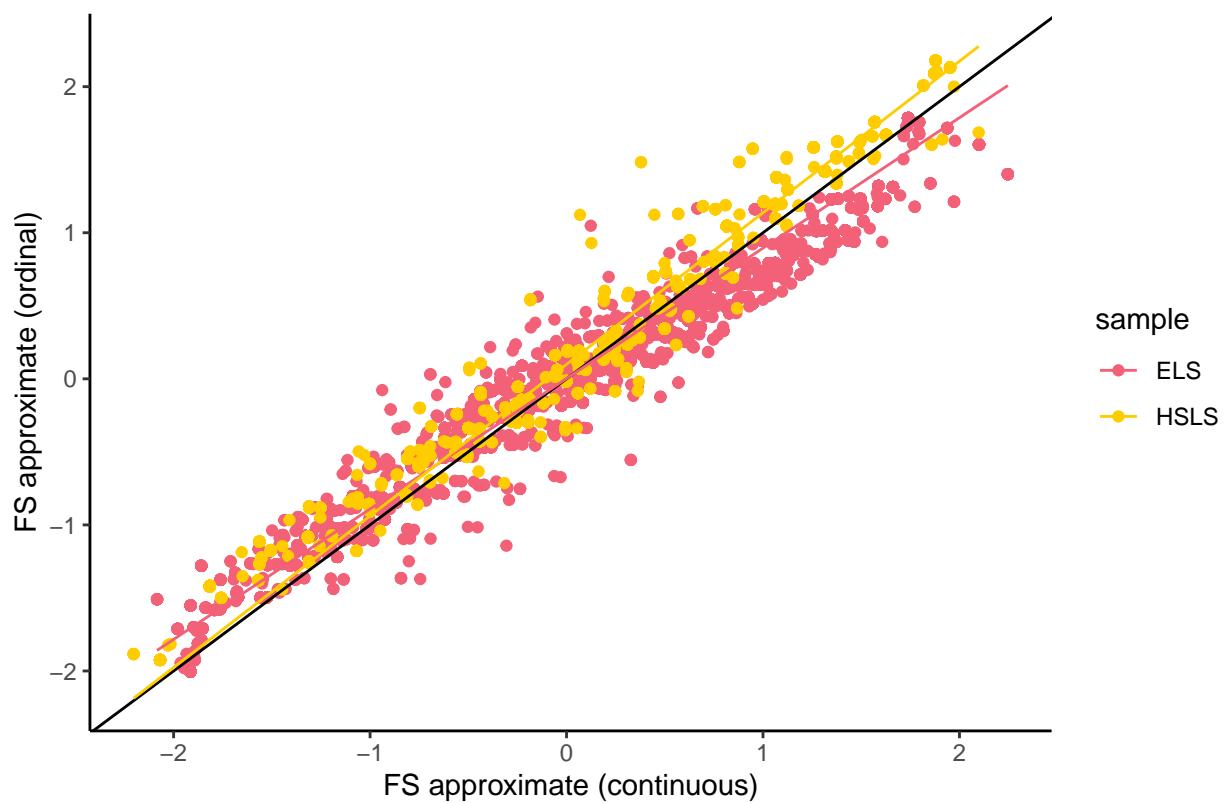
[No NAs] Correlation of FS: partial (cont.; M4) or approximate (cont.; M5)



[No NAs] Correlation of FS: partial (ord.; M6) or approximate (ord.; M7)



Correlation of FS: approximate (cont.; M2) vs. approximate (ord.; M3)



[No NAs] Correlation of FS: partial (cont.; M4) or partial (ord.; M6)

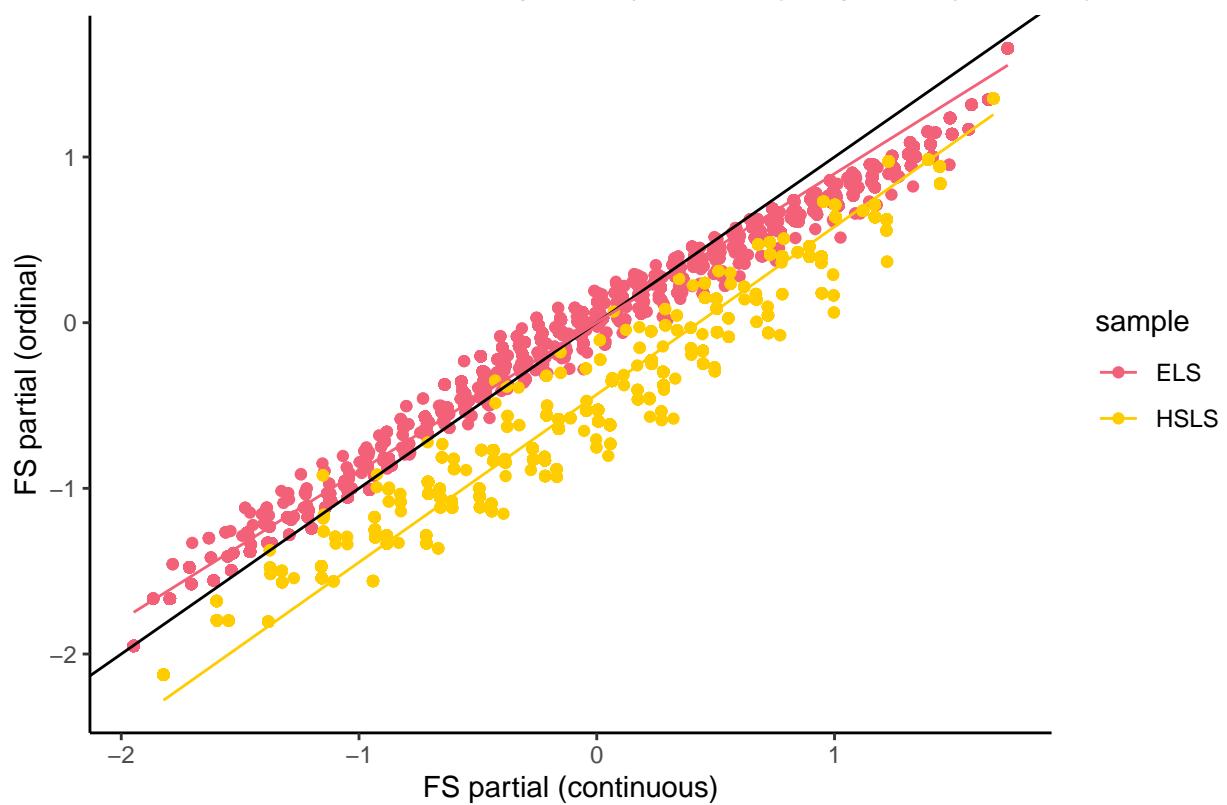
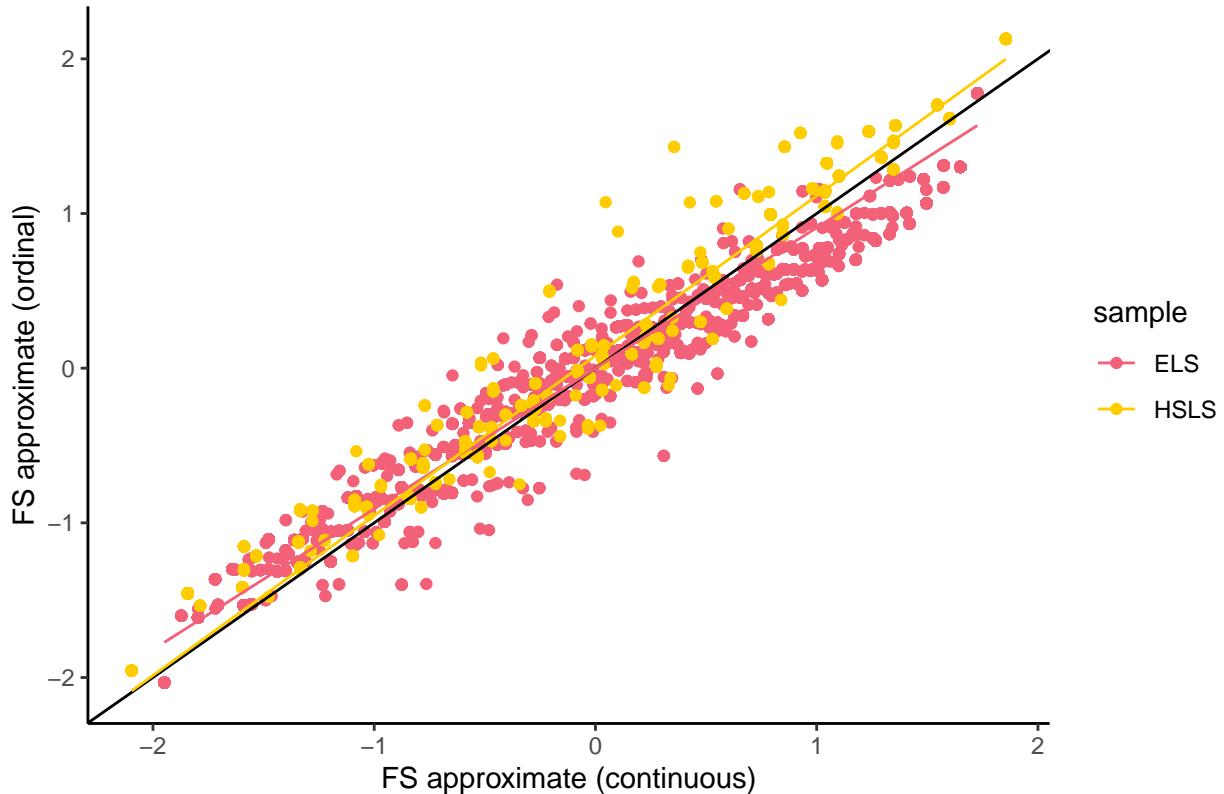


Table 9: Mean and SD of FS Reliabilities (N = 30,740)

	Continuous				Ordinal			
	Partial		Approximate		Partial		Approximate	
	ELS	HSLS	ELS	HSLS	ELS	HSLS	ELS	HSLS
Mean	0.9139	0.9195	0.914	0.9193	-	-	0.9068	0.8833
SD	0.0515	0.0102	0.0519	0.0102	-	-	0.0668	0.0418

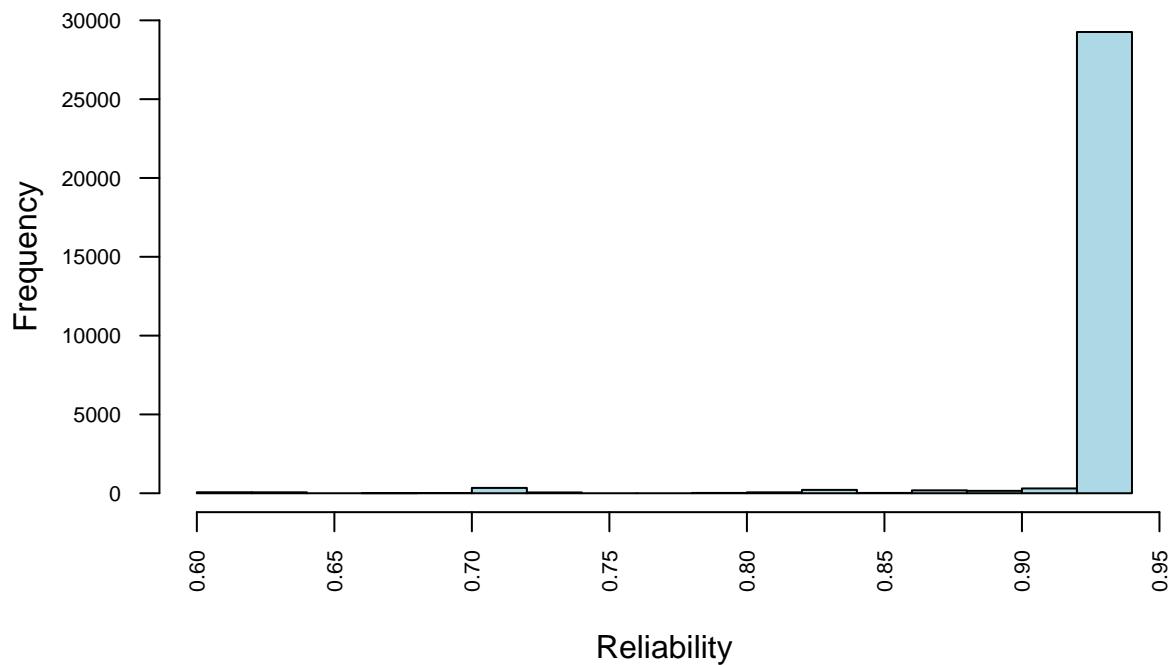
[No NAs] Correlation of FS: approx. (cont.; M5) or approx. (ord.; M7)



Reliability

```
mnsd(df$partial_rel)
## [1] 0.91736732 0.03280564
mnsd(df$approx_rel)
## [1] 0.91732712 0.03304773
mnsd(df$approx_ord_rel)
## [1] 0.89223975 0.05391562
```

Reliability of Bartlett factor scores (partial inv.; cont.)



Reliability of Bartlett factor scores (approx. inv.; cont.)

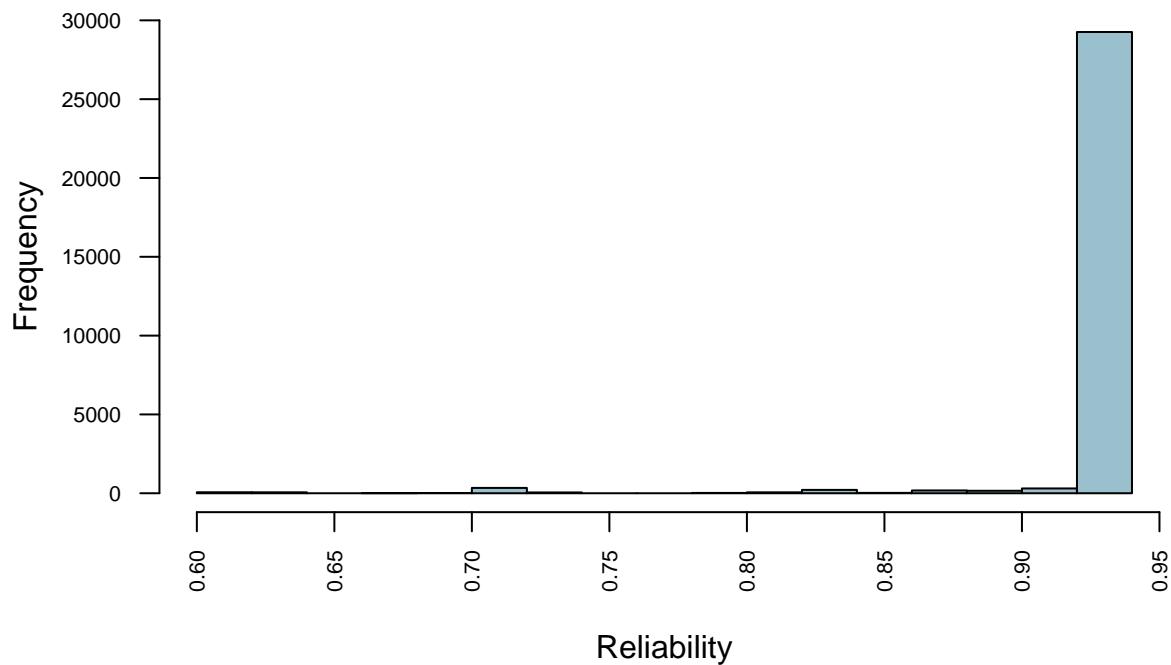
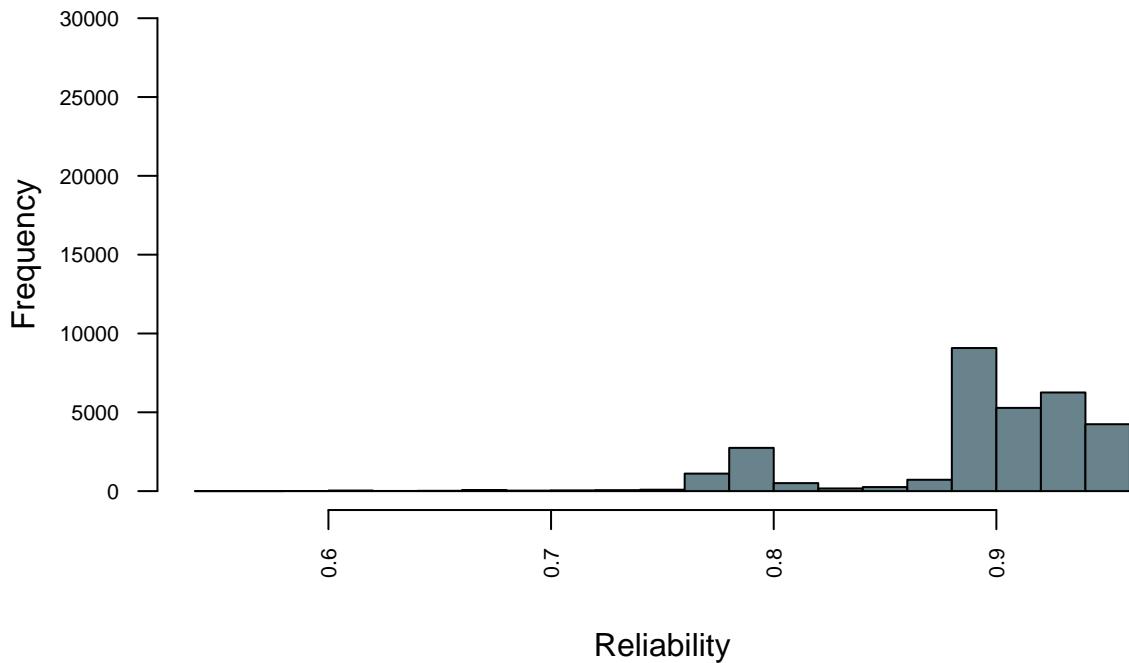


Table 10: Correlation of FS Reliabilities (N = 30,740)

	Continuous		Ordinal	
	Partial	Approximate	Partial	Approximate
	M1	M2	-	M3
M1	1	0.9999	-	0.3952
M2	0.9999	1	-	0.3971
-	-	-	-	-
M3	0.3952	0.3971	-	1

Reliability of EAP factor scores (approx. inv.; ordinal)

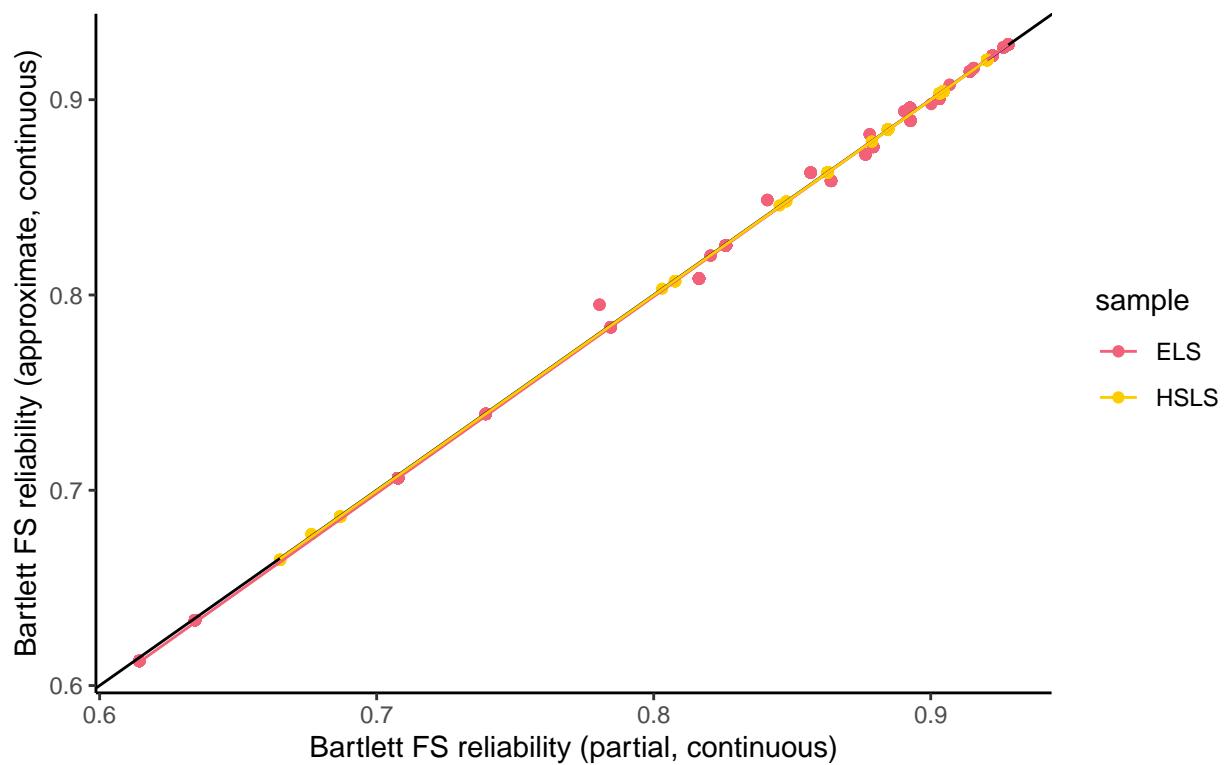


```

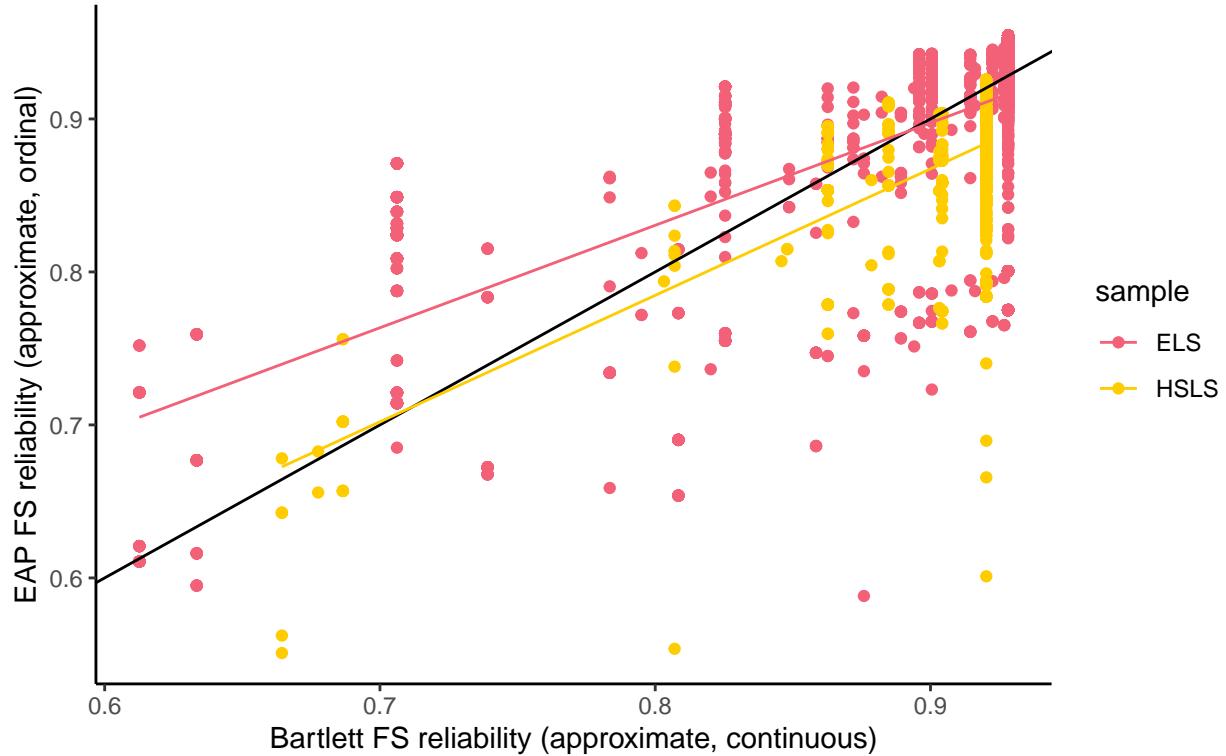
rel_30749 <- cor(as.matrix(apply(df[ ,c("partial_rel",
                                         "approx_rel",
                                         "approx_ord_rel")],
                                         as.numeric, MARGIN = 2)),
                  use = "complete.obs")
rel_30749 <- round(rel_30749, 4)
rel_30749_add_row <- rbind(rel_30749[1:2,], rep("-",3) , rel_30749[3,])
rel_30749_add_col <- cbind(rel_30749_add_row[,1:2] , rep("-",4) , rel_30749_add_row[,3])
colnames(rel_30749_add_col) <- rownames(rel_30749_add_col) <- as.character(models[1,])[2:5]

```

Correlation of reliability of factor scores computed using
MI modeling or alignment



Correlation of reliability of factor scores computed using continuous or ordinal alignment



Dmacs effect sizes of noninvariance

We use the R package `pinsearch` to compute the Dmacs effect size of noninvariance for each approach. We use the `pin_effsize()` function and `dmacs_ordered()` for the ordinal case. Note that if there are more than two groups, `pin_effsize()` computes the Fmacs effect size when data are continuous, and `fmacs_ordered()` should replace `dmacs_ordered()` in the ordinal case.

Continuous case

```
dmacs_partial <- pinsearch::pin_effsize(fit_partial)
dmacs_align <- pinsearch::pin_effsize(fit_align)
```

Ordinal case

```
# indicate which thresholds belong to which item
est_align_ord_th_sub <- est_align_ord_th[, -c(3, 8, 13)]
colnames(est_align_ord_th_sub) <- rep(c(1, 2, 4, 5), 3)

# compute pooled SD for dmacs_ordered()
vars <- apply(dat[m_items], MARGIN = 2,
              FUN = \((x)\) tapply(x, INDEX = dat$sample, FUN = var, na.rm = TRUE)
              )
(wgt_mat <- as.matrix(rbind(
  colSums(!is.na(dat[dat$sample=="ELS", m_items])),
  colSums(!is.na(dat[dat$sample=="HSLS", m_items]))
```

```

)))
##      i1    i2    i3    i4    i5
## [1,] 11391 11432 11047 10823 10661
## [2,] 19049 19006      0 18926 18976
item_n <- ifelse(wgt_mat > 0, wgt_mat, NA)
pooled_sd <- sqrt(colSums(vars * (item_n - 1), na.rm = TRUE) /
  colSums(item_n - 1, na.rm = TRUE)
)

dmacs_align_ord <- pinsearch::dmacs_ordered(
  thresholds = as.matrix(est_align_ord_th_sub),
  loadings = as.matrix(est_align_ord_lam)[, -3],
  link = "logit",
  pooled_item_sd = pooled_sd[-3]
)

# compute dmacs effect size for ordinal MI modeling approach:
# first recompute pooled SD since rows with NAs had to be dropped in the ordinal
# MI modeling approach
## note that now we're using d_noNAs as out dataset.

vars_noNAs <- apply(d_noNAs[m_items], MARGIN = 2,
  FUN = \x) tapply(x, INDEX = d_noNAs$sample,
  FUN = var, na.rm = TRUE)
)
(wgt_mat_noNAs <- as.matrix(rbind(
  colSums(!is.na(d_noNAs[d_noNAs$sample=="ELS", m_items])),
  colSums(!is.na(d_noNAs[d_noNAs$sample=="HSLS", m_items]))
))

##      i1    i2    i3    i4    i5
## [1,] 10443 10443 10443 10443 10443
## [2,] 18759 18759      0 18759 18759
item_n_noNAs <- ifelse(wgt_mat_noNAs > 0, wgt_mat_noNAs, NA)
pooled_sd_noNAs <- sqrt(colSums(vars_noNAs * (item_n_noNAs - 1), na.rm = TRUE) /
  colSums(item_n_noNAs - 1, na.rm = TRUE)
)

# indicate which thresholds belong to which item
est_partial_ord_th_sub <- as.matrix(rbind(t(est_partial_ord$ELS$tau)[-c(7:9)],
  t(est_partial_ord$HSL$tau)))
colnames(est_partial_ord_th_sub) <- c(rep(1, 3), rep(2, 3), rep(4, 3), rep(5, 3))
est_partial_ord_lam <- as.matrix(rbind(t(est_partial_ord$ELS$lambda)[-3],
  t(est_partial_ord$HSL$lambda)))

dmacs_partial_ord <- pinsearch::dmacs_ordered(
  thresholds = est_partial_ord_th_sub,
  loadings = est_partial_ord_lam,
  link = "logit",
  pooled_item_sd = pooled_sd_noNAs[-3]
)

```

Table 11: Dmacs effect sizes of noninvariance by approach (N = 30,749)

	Continuous		Ordinal	
	Partial (M1)	Approximate (M2)	-	Approximate (M3)
i1	0.149	0.072	-	0.217
i2	0.219	0.09	-	0.206
i4	-	0.137	-	0.267
i5	-	0.15	-	0.311

Table 12: Dmacs effect sizes of noninvariance by approach (N = 29,202)

	Continuous		Ordinal	
	Partial (M4)	Approximate (M5)	Partial (M6)	Approximate (M7)
i1	0.147	0.079	0.212	0.208
i2	0.215	0.091	0.113	0.187
i4	-	0.133	0.263	0.263
i5	-	0.145	0.142	0.298