sim_fmacs_p=6_b

```
Setup for simulation
  library(dplyr)
Attaching package: 'dplyr'
The following objects are masked from 'package:stats':
    filter, lag
The following objects are masked from 'package:base':
    intersect, setdiff, setequal, union
  library(ggplot2)
Warning: package 'ggplot2' was built under R version 4.3.3
  library(gt)
Warning: package 'gt' was built under R version 4.3.3
  library(knitr)
Warning: package 'knitr' was built under R version 4.3.3
```

library(lavaan)

```
Warning: package 'lavaan' was built under R version 4.3.3

This is lavaan 0.6-18
lavaan is FREE software! Please report any bugs.
```

```
library(pinsearch)
library(SimDesign)
```

Warning: package 'SimDesign' was built under R version 4.3.3

```
# TODO:
# - Summarize the pattern of bias
# Define conditions: Testing different sample sizes
design <- createDesign(</pre>
  n = c(30, 100, 250, 1000)
# Fixed objects
set.seed(1855)
# Helper
get_ucov <- function(p, scale = sqrt(0.1), n = 5) {</pre>
  W <- matrix(rnorm(p * n), nrow = n)</pre>
  WtW <- crossprod(W)</pre>
  D <- diag(1 / sqrt(diag(WtW))) * scale</pre>
  D %*% WtW %*% D
fixed <- list(</pre>
  lambda = c(.3, .7, .4, .5, .6, .4),
  dlambda = list(
    c(0, 0, 0, 0, 0, 0),
    c(.1, 0, 0, 0, 0, 0),
    c(.2, -.3, 0, 0, 0, 0),
    c(.3, -.3, 0, 0, 0, 0)
  ),
```

```
nu = c(2, 3, 1.5, 3.5, 2, 3),
  alpha = c(0, -0.25, 0.25, 0.5),
  psi = c(1, 0.85, 1.15, 0.7),
  theta = c(1, 1.2, .8, .9, 1, 1) - .1,
  dtheta = matrix(
    runif(24, min = -0.2, max = 0.2),
    nrow = 4
  ),
  # ucov = replicate(4, get_ucov(6), simplify = FALSE)
  ucov = replicate(4, diag(.1, 6), simplify = FALSE),
  ninv_ind = c(1, 2)
# lavaan syntax
fixed$mod <- paste(</pre>
  "f =~",
  paste0("y", seq_len(fixed$p), collapse = " + ")
# Compute implied means and covariances
fixed <- within(fixed, {</pre>
  lambdag <- lapply(dlambda, FUN = \(x) x + lambda)
  Thetag <- lapply(seq_along(ucov),</pre>
                    FUN = function(g) {
                      diag(theta + dtheta[g, ]) + ucov[[g]]
  covy <- mapply(\((lam, psi, th) tcrossprod(lam) * psi + th,</pre>
                  lam = lambdag, psi = psi, th = Thetag,
                  SIMPLIFY = FALSE)
  meany <- mapply(\((lam, al, nu) nu + lam * al,</pre>
                   lam = lambdag, al = alpha, nu = list(nu),
                   SIMPLIFY = FALSE)
})
# Population effect size
fixed$fmacs_pop <- local({</pre>
  pooled_sd <- lapply(fixed$covy, FUN = \(x) diag(x)) |>
    do.call(what = rbind) |>
    colMeans() |>
    sqrt()
  fmacs(
    intercepts = matrix(rep(fixed$nu, 4),
```

```
nrow = 4,
                            byrow = TRUE
      ),
      loadings = sweep(
        do.call(rbind, fixed$dlambda),
        MARGIN = 2,
        STATS = fixed$lambda,
        FUN = "+"
      ),
      latent_mean = 0,
      latent_sd = 1,
      pooled_item_sd = pooled_sd
    )[1:2]
  })
  # Function for data generation
  # sim_y <- function(n, lambda, nu, alpha, psi, Theta) {</pre>
         covy <- tcrossprod(lambda) * psi + Theta</pre>
        meany <- nu + lambda * alpha
        MASS::mvrnorm(n, mu = meany, Sigma = covy)
  # }
Running the simulation
  generate <- function(condition, fixed_objects) {</pre>
    ylist <- lapply(seq_along(fixed_objects$covy),</pre>
                     FUN = function(g) {
                        yg <- MASS::mvrnorm(</pre>
                          condition$n,
                          mu = fixed_objects$meany[[g]],
                          Sigma = fixed_objects$covy[[g]]
                        colnames(yg) <- paste0("y", seq_len(fixed_objects$p))</pre>
                        cbind(yg, group = g)
    do.call(rbind, ylist)
  sim1 <- generate(design[3, ], fixed_objects = fixed)</pre>
  # Analysis
```

```
analyze <- function(condition, dat, fixed_objects) {</pre>
  # Define lavaan syntax
 pinv_fit <- cfa(</pre>
    fixed_objects$mod,
    data = dat,
    group = "group", std.lv = TRUE,
    group.equal = c("loadings", "intercepts"),
    group.partial = c(
      paste0("f=~y", fixed_objects$ninv_ind),
      paste0("y", fixed_objects$ninv_ind, "~1")
    )
  )
  as.vector(pinsearch::pin_effsize(pinv_fit))
}
analyze_bc <- function(condition, dat, fixed_objects) {</pre>
  # Define lavaan syntax
 pinv_fit <- cfa(</pre>
    fixed_objects$mod,
    data = dat,
    group = "group", std.lv = TRUE,
    group.equal = c("loadings", "intercepts"),
    group.partial = c(
      paste0("f=~y", fixed_objects$ninv_ind),
      paste0("y", fixed_objects$ninv_ind, "~1")
    )
  f_orig <- as.vector(pinsearch::pin_effsize(pinv_fit))</pre>
  f_boot <- lavaan::bootstrapLavaan(pinv_fit,</pre>
                                      FUN = pinsearch::pin_effsize
  )
 pmax(0, 2 * f_orig - colMeans(f_boot, na.rm = TRUE))
analyze_bc2 <- function(condition, dat, fixed_objects) {</pre>
  # Define lavaan syntax
 pinv_fit <- cfa(</pre>
    fixed_objects$mod,
    data = dat,
    group = "group", std.lv = TRUE,
```

```
group.equal = c("loadings", "intercepts"),
    group.partial = c(
      paste0("f=~y", fixed_objects$ninv_ind),
      paste0("y", fixed_objects$ninv_ind, "~1")
    )
  )
  f_orig <- pinsearch::pin_effsize(pinv_fit)</pre>
  ns <- lavInspect(pinv_fit, what = "nobs")</pre>
  ng <- length(ns)
  f2_bias <- (ng - 1) / ng * sum(1 / ns)
  sqrt(pmax(0, f_orig^2 - f2_bias))
}
# Evaluate/Summarize
evaluate <- function(condition, results, fixed_objects) {</pre>
    bias = colMeans(results) - fixed_objects$fmacs_pop,
    robust_bias = apply(results, 2, mean, trim = .1) -
      fixed_objects$fmacs_pop,
    emp_sd = apply(results, 2, sd),
    emp_mad = apply(results, 2, mad)
  )
}
out <- runSimulation(design,</pre>
                       replications = 500,
                       parallel = TRUE,
                       ncores = parallelly::availableCores(omit = 3L),
                       generate = generate,
                       analyse = list(naive = analyze,
                                      bc_boot = analyze_bc,
                                      bc_form = analyze_bc2),
                       summarise = evaluate,
                       filename = "results-trial-bc",
                       packages = c("MASS", "lavaan", "pinsearch"),
                       fixed_objects = fixed,
                       save_results = TRUE)
```

Number of parallel clusters in use: 17

```
./results-trial-bc-results_DESKTOP-342341B already exists; using ./results-trial-bc-results_1
```

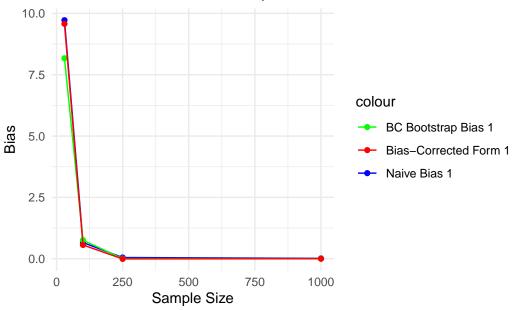
```
Design: 1/4;
              RAM Used: 71.9 Mb; Replications: 500;
                                                         Total Time: 0.00s
 Conditions: n=30
Design: 2/4;
               RAM Used: 72.6 Mb; Replications: 500;
                                                         Total Time: 02h 55m 52.31s
 Conditions: n=100
Design: 3/4;
               RAM Used: 72.6 Mb;
                                    Replications: 500;
                                                         Total Time: 03h 24m 32.06s
 Conditions: n=250
Design: 4/4;
               RAM Used: 72.6 Mb; Replications: 500;
                                                         Total Time: 03h 40m 46.13s
 Conditions: n=1000
Simulation complete. Total execution time: 03h 56m 37.17s
Saving simulation results to file: results-trial-bc.rds
  data <- readRDS("C:/Users/alex/OneDrive/Desktop/results-trial-bc.rds")</pre>
Graphs to visualize simulation results
  # Bias
  bias_plot <- ggplot(data, aes(x = n)) +
    geom_line(aes(y = bias.naive1, color = "Naive Bias 1")) +
    geom_point(aes(y = bias.naive1, color = "Naive Bias 1")) +
    geom_line(aes(y = bias.bc_boot1, color = "BC Bootstrap Bias 1")) +
    geom_point(aes(y = bias.bc_boot1, color = "BC Bootstrap Bias 1")) +
    geom_line(aes(y = bias.bc_form1, color = "Bias-Corrected Form 1")) +
    geom_point(aes(y = bias.bc_form1, color = "Bias-Corrected Form 1")) +
    labs(title = "Bias for Naive, BC Bootstrap, and Bias-Corrected across Sample Sizes",
         x = "Sample Size", y = "Bias") +
```

"BC Bootstrap Bias 1" = "green",

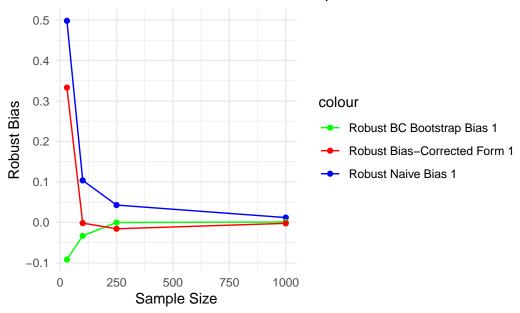
scale_color_manual(values = c("Naive Bias 1" = "blue",

```
"Bias-Corrected Form 1" = "red")) +
theme_minimal()
bias_plot
```

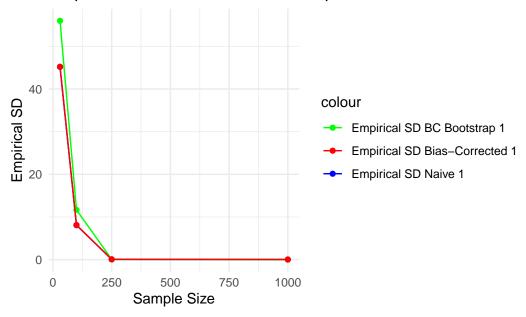
Bias for Naive, BC Bootstrap, and Bias-Corrected across San



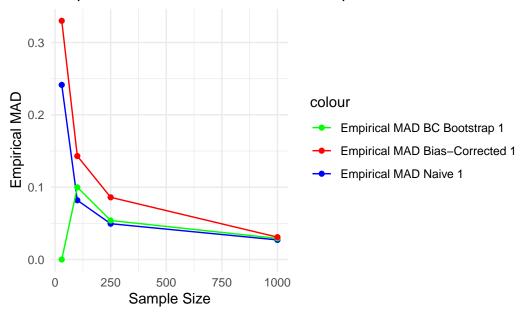
Robust Bias for Naive, BC Bootstrap, and Bias-Corrected acro



Empirical SD for Naive, BC Bootstrap, and Bias-Corrected acrc



Empirical MAD for Naive, BC Bootstrap, and Bias-Corrected ac



Set up for tables

```
bias_table <- data.frame(</pre>
  SampleSize = data$n,
  Bias_Naive1 = data$bias.naive1,
  Bias_BC_Boot1 = data$bias.bc_boot1,
  Bias_BC_Form1 = data$bias.bc_form1
)
robust_bias_table <- data.frame(</pre>
  SampleSize = data$n,
  Robust_Bias_Naive1 = data$robust_bias.naive1,
  Robust_Bias_BC_Boot1 = data$robust_bias.bc_boot1,
  Robust_Bias_BC_Form1 = data$robust_bias.bc_form1
)
emp_sd_table <- data.frame(</pre>
  SampleSize = data$n,
  Empirical_SD_Naive1 = data$emp_sd.naive1,
  Empirical_SD_BC_Boot1 = data$emp_sd.bc_boot1,
  Empirical_SD_BC_Form1 = data$emp_sd.bc_form1
)
```

```
Empirical_MAD_Naive1 = data$emp_mad.naive1,
    Empirical_MAD_BC_Boot1 = data$emp_mad.bc_boot1,
    Empirical_MAD_BC_Form1 = data$emp_mad.bc_form1
)

# Create and display tables using knitr
knitr::kable(bias_table, caption = "Bias for Naive, BC Bootstrap, and Bias-Corrected across)
```

Table 1: Bias for Naive, BC Bootstrap, and Bias-Corrected across Sample Sizes

emp_mad_table <- data.frame(
 SampleSize = data\$n,</pre>

SampleSize	Bias_Naive1	Bias_BC_Boot1	Bias_BC_Form1
30	9.7218803	8.1710552	9.5740247
100	0.6569590	0.7541530	0.5600170
250	0.0477572	0.0033855	-0.0090273
1000	0.0129750	0.0017650	-0.0019629

knitr::kable(robust_bias_table, caption = "Robust Bias for Naive, BC Bootstrap, and Bias-C

Table 2: Robust Bias for Naive, BC Bootstrap, and Bias-Corrected across Sample Sizes

SampleSize	Robust_Bias_Naive1	Robust_Bias_BC_Boot1	Robust_Bias_BC_Form1
30	0.4980913	-0.0918035	0.3331221
100	0.1037743	-0.0332902	-0.0018570
250	0.0427538	-0.0002190	-0.0158307
1000	0.0118461	0.0008494	-0.0024153

knitr::kable(emp_sd_table, caption = "Empirical Standard Deviation for Naive, BC Bootstrap

Table 3: Empirical Standard Deviation for Naive, BC Bootstrap, and Bias-Corrected across Sample Sizes

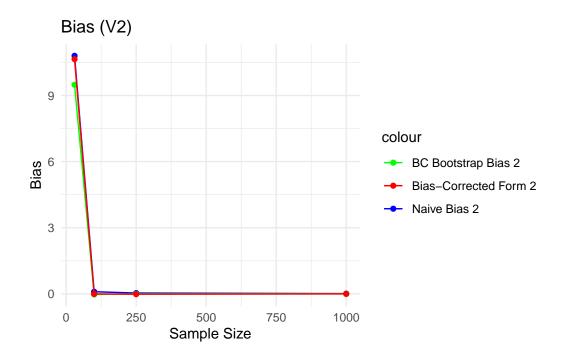
SampleSize	Empirical_SD_Naive1	${\bf Empirical_SD_BC_Boot1\ Empirical_}$	SD_BC_Form1
30	45.1790360	55.9852546	45.2100767
100	8.0936589	11.6736326	8.1006171
250	0.0552012	0.0577781	0.0769428

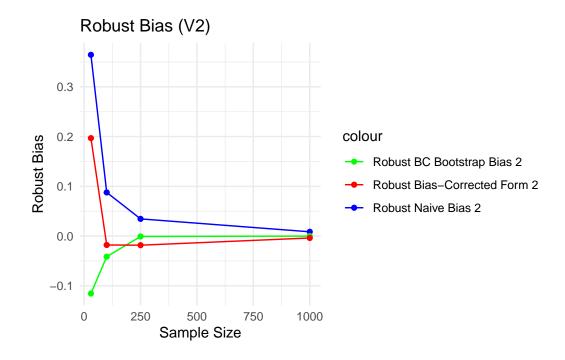
SampleSize	Empirical_SD_Naive1	${\bf Empirical_SD_BC_Boot1\ Empirical}$	_SD_BC_Form1
1000	0.0273751	0.0291286	0.0319034

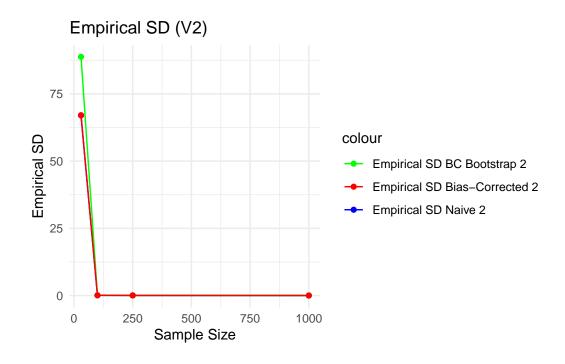
```
knitr::kable(emp_mad_table, caption = "Empirical MAD for Naive, BC Bootstrap, and Bias-Cor
```

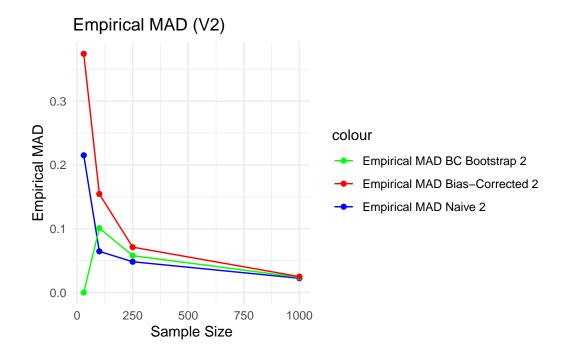
Table 4: Empirical MAD for Naive, BC Bootstrap, and Bias-Corrected across Sample Sizes

SampleSize	Empirical_MAD_Naive1Empirical_	_MAD_BC_BootImpirical	_MAD_BC_Form1
30	0.2414609	0.0000000	0.3300305
100	0.0819243	0.0998460	0.1430580
250	0.0495064	0.0539396	0.0860082
1000	0.0270873	0.0292359	0.0309464









```
bias_table_2 <- data.frame(
    SampleSize = data$n,
    Bias_Naive2 = data$bias.naive2,
    Bias_BC_Boot2 = data$bias.bc_boot2,
    Bias_BC_Form2 = data$bias.bc_form2
)

robust_bias_table_2 <- data.frame(
    SampleSize = data$n,
    Robust_Bias_Naive2 = data$robust_bias.naive2,
    Robust_Bias_BC_Boot2 = data$robust_bias.bc_boot2,
    Robust_Bias_BC_Form2 = data$robust_bias.bc_form2
)

emp_sd_table_2 <- data.frame(
    SampleSize = data$n,
    Empirical_SD_Naive2 = data$emp_sd.naive2,
    Empirical_SD_BC_Boot2 = data$emp_sd.bc_boot2,
    Empirical_SD_BC_Form2 = data$emp_sd.bc_form2
)</pre>
```

```
emp_mad_table_2 <- data.frame(
    SampleSize = data$n,
    Empirical_MAD_Naive2 = data$emp_mad.naive2,
    Empirical_MAD_BC_Boot2 = data$emp_mad.bc_boot2,
    Empirical_MAD_BC_Form2 = data$emp_mad.bc_form2
)

# Create and display tables using knitr
knitr::kable(bias_table_2, caption = "Bias V2")</pre>
```

Table 5: Bias V2

SampleSize	Bias_Naive2	Bias_BC_Boot2	Bias_BC_Form2
30	10.7996025	9.4862657	10.6487700
100	0.0948459	-0.0316131	-0.0048182
250	0.0353780	-0.0013300	-0.0177776
1000	0.0092022	0.0002600	-0.0035215

```
knitr::kable(robust_bias_table_2, caption = "Robust Bias V2")
```

Table 6: Robust Bias V2

SampleSize	Robust_Bias_Naive2	Robust_Bias_BC_Boot2	Robust_Bias_BC_Form2
30	0.3644530	-0.1155737	0.1969064
100	0.0876955	-0.0414437	-0.0179622
250	0.0345028	-0.0008506	-0.0183926
1000	0.0085595	-0.0001209	-0.0039114

```
knitr::kable(emp_sd_table_2, caption = "Empirical Standard Deviation V2")
```

Table 7: Empirical Standard Deviation V2

SampleSize	Empirical_SD_Naive2	${\bf Empirical_SD_BC_Boot2\ Empirical}$	_SD_BC_Form2
30	67.0112165	88.7801769	67.0350284
100	0.0819323	0.0851897	0.1130994
250	0.0450277	0.0538186	0.0656115
1000	0.0230113	0.0245284	0.0256151

knitr::kable(emp_mad_table_2, caption = "Empirical MAD V2")

Table 8: Empirical MAD V2 $\,$

SampleSize	Empirical_MAD_Naive2Empirical	_MAD_BC_Booft2mpir	ical_MAD_BC_Form2
30	0.2150856	0.0000000	0.3741931
100	0.0645431	0.1008793	0.1545591
250	0.0482424	0.0577743	0.0711156
1000	0.0223497	0.0238004	0.0249093