# 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, 5000)
# 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),
```

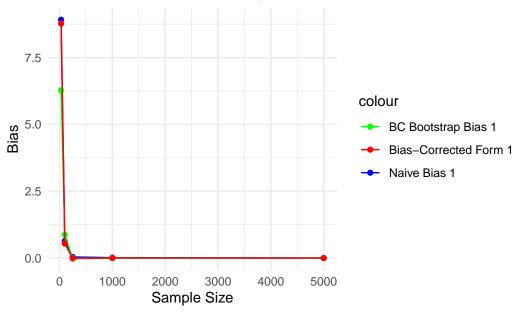
```
nrow = 4,
                            byrow = TRUE
      ),
      loadings = sweep(
        do.call(rbind, fixed$dlambda),
        MARGIN = 2,
        STATS = fixed$lambda,
        FUN = "+"
      ),
      latent_mean = 0,
      latent_sd = 1,
      pooled_item_sd = pooled_sd
    )[1:2]
  })
  # 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 = 250,
                        parallel = TRUE,
                        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
# )
data <- readRDS("C:/Users/alex/OneDrive/Documents/results-trial-bc.rds")</pre>
```

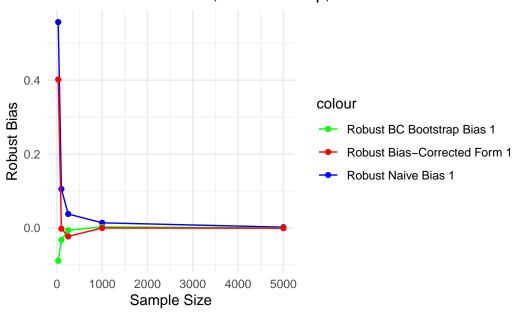
Graphs to visualize simulation results

# Bias for Naive, BC Bootstrap, and Bias-Corrected across Sam



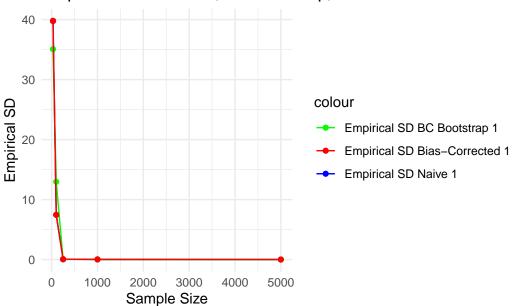
```
# Robust Bias
robust_bias_plot <- ggplot(data, aes(x = n)) +
   geom_line(aes(y = robust_bias.naive1, color = "Robust Naive Bias 1")) +
   geom_point(aes(y = robust_bias.naive1, color = "Robust Naive Bias 1")) +
   geom_line(aes(y = robust_bias.bc_boot1, color = "Robust BC Bootstrap Bias 1")) +</pre>
```

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

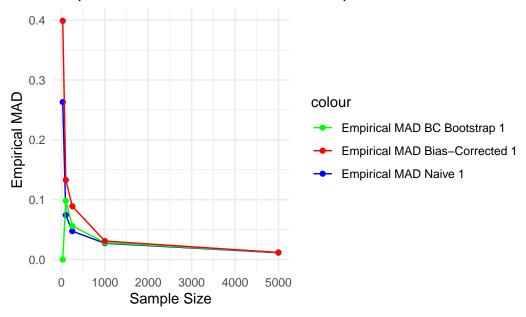


```
# Empirical Standard Deviation
emp_sd_plot <- ggplot(data, aes(x = n)) +
    geom_line(aes(y = emp_sd.naive1, color = "Empirical SD Naive 1")) +
    geom_point(aes(y = emp_sd.naive1, color = "Empirical SD Naive 1")) +
    geom_line(aes(y = emp_sd.bc_boot1, color = "Empirical SD BC Bootstrap 1")) +
    geom_point(aes(y = emp_sd.bc_boot1, color = "Empirical SD BC Bootstrap 1")) +
    geom_line(aes(y = emp_sd.bc_form1, color = "Empirical SD Bias-Corrected 1")) +
    geom_point(aes(y = emp_sd.bc_form1, color = "Empirical SD Bias-Corrected 1")) +
    labs(title = "Empirical SD for Naive, BC Bootstrap, and Bias-Corrected across Sample Siz
    x = "Sample Size", y = "Empirical SD") +</pre>
```

#### 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	8.9145626	6.2761694	8.7733024
100	0.6400178	0.8718441	0.5412443
250	0.0417918	-0.0037044	-0.0163374
1000	0.0148040	0.0034603	0.0000516
5000	0.0022918	0.0000941	-0.0006132

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

${\bf Sample Size}$	Robust_Bias_Naive1	Robust_Bias_BC_Boot1	Robust_Bias_BC_Form1
30	0.5573468	-0.0893366	0.4020016
100	0.1050621	-0.0329775	-0.0023121
250	0.0375246	-0.0065947	-0.0232138
1000	0.0136022	0.0024601	-0.0004156
5000	0.0019113	-0.0002633	-0.0009805

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

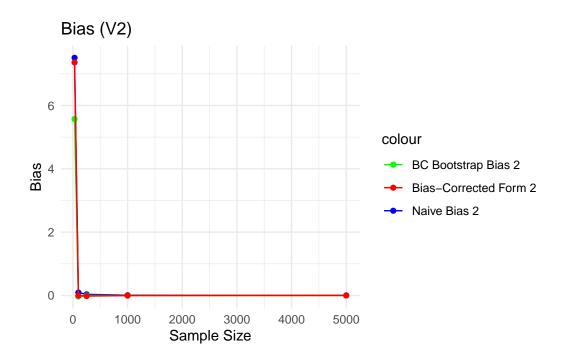
SampleSize	Empirical_SD_Naive1	${\bf Empirical\_SD\_BC\_Boot1\ Empirical}$	SD_BC_Form1
30	39.7623512	35.0814255	39.7931779

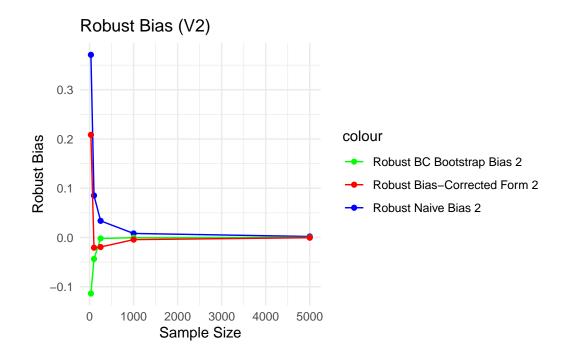
SampleSize	Empirical_SD_Naive1	${\bf Empirical\_SD\_BC\_Boot1\ Empirical\_}$	SD_BC_Form1
100	7.4620651	12.9672387	7.4695273
250	0.0526387	0.0561582	0.0738196
1000	0.0283332	0.0300447	0.0329846
5000	0.0122437	0.0124034	0.0125824

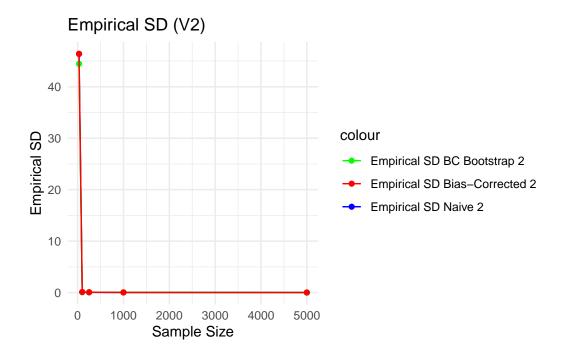
knitr::kable(emp\_mad\_table, caption = "Empirical MAD for Naive, BC Bootstrap, and Bias-Cor

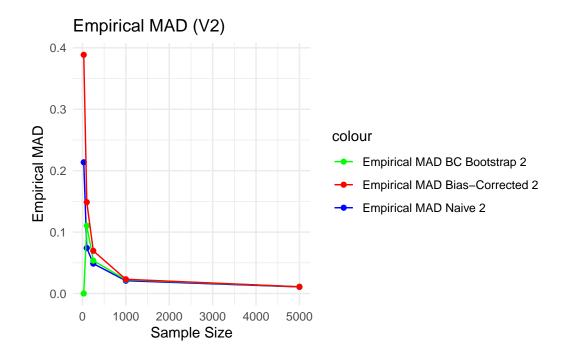
Table 4: Empirical MAD for Naive, BC Bootstrap, and Bias-Corrected across Sample Sizes

SampleSize	Empirical_MAD_Naive1Empirical_	_MAD_BC_BootImpirical	MAD_BC_Form1
30	0.2631611	0.0000000	0.3988596
100	0.0743302	0.0981924	0.1329826
250	0.0473194	0.0560259	0.0889281
1000	0.0271608	0.0282376	0.0308964
5000	0.0114088	0.0117638	0.0117348









```
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	7.5049551	5.5723037	7.3590679
100	0.0923597	-0.0339516	-0.0067817
250	0.0339720	-0.0025279	-0.0194599
1000	0.0085489	-0.0003854	-0.0042759
5000	0.0023826	0.0005272	-0.0001138

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	0.3710510	-0.1137912	0.2084884
100	0.0851987	-0.0436170	-0.0206891
250	0.0338193	-0.0019940	-0.0193453
1000	0.0081941	-0.0004234	-0.0042959
5000	0.0020354	0.0002098	-0.0004568

knitr::kable(emp\_sd\_table\_2, caption = "Empirical Standard Deviation V2")

Table 7: Empirical Standard Deviation V2

SampleSize	Empirical_SD_Naive2	Empirical_SD_BC_Boot2 Empirical_	_SD_BC_Form2
30	46.3900953	44.4591444	46.4130000
100	0.0820824	0.0813790	0.1126055
250	0.0433286	0.0517182	0.0639713

SampleSize	${\bf Empirical\_SD\_Naive2}$	${\bf Empirical\_SD\_BC\_Boot2\ Empirical}$	_SD_BC_Form2
1000	0.0230168	0.0247583	0.0257574
5000	0.0108980	0.0110963	0.0111199

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	0.2136893	0.0000000	0.3886024
100	0.0740743	0.1104595	0.1486673
250	0.0486501	0.0535134	0.0694642
1000	0.0208017	0.0225060	0.0231825
5000	0.0107347	0.0109490	0.0109717