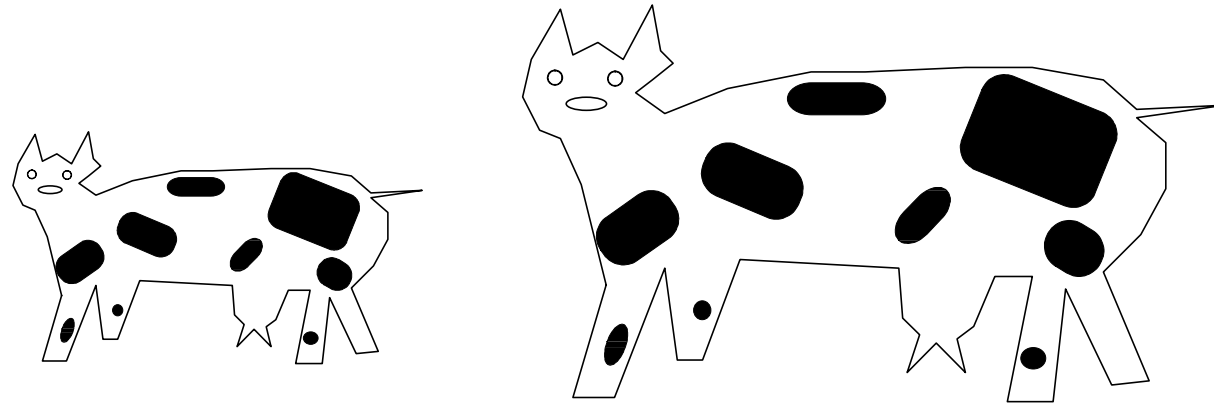


**Bootstrap confidence intervals —
ein **statistisches** Werkzeug für
landwirtschaftliche und biologische Versuche**

Manfred Mudelsee

Institute of Meteorology, University of Leipzig, FRG



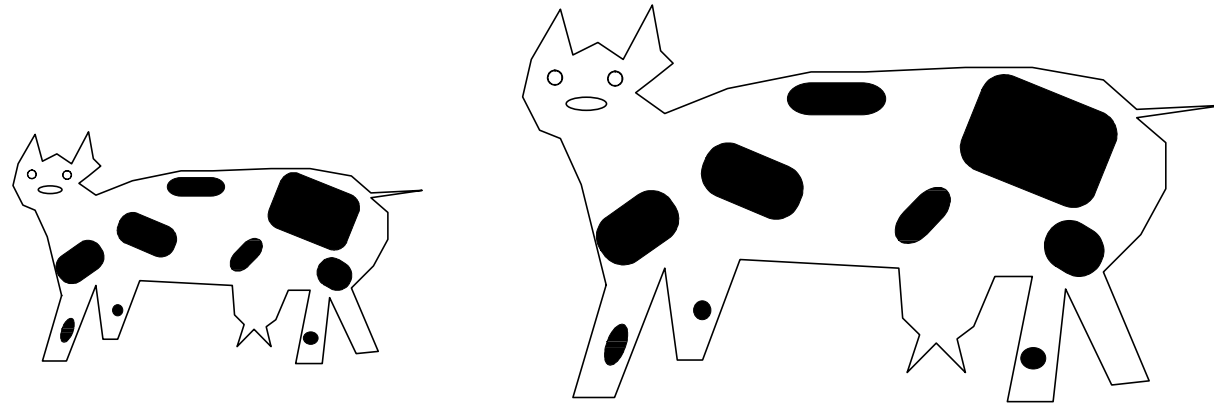
Exact case

Hypothesis: “Cow on the right (with SUPERFEED™) is heavier.”

vs.

Estimate: “Cow on the right (with SUPERFEED™) is heavier
by 1.5 tons.”

⇒ surplus information



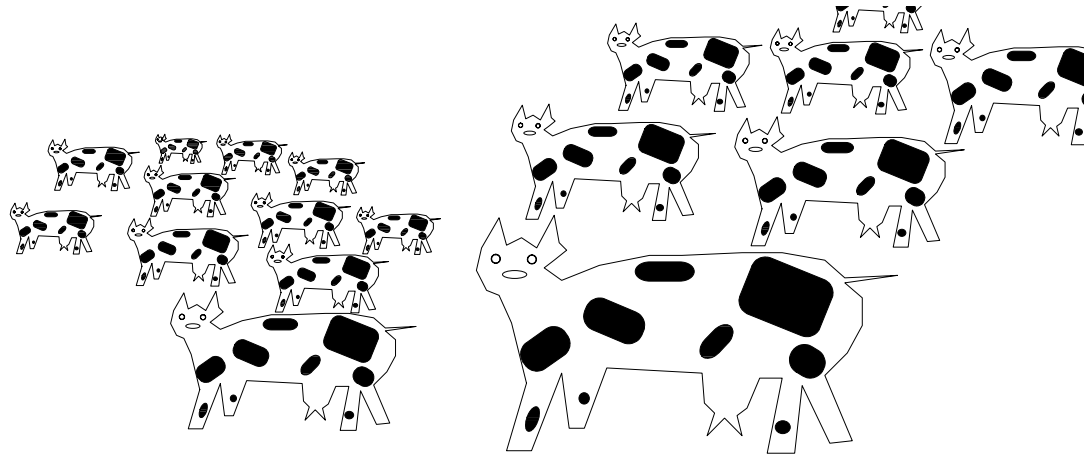
Uncertain case: **statistics**

Hypothesis: “Cow on the right (with SUPERFEED™) is heavier
(at significance level 0.9).”

vs.

Estimate: “Cow on the right (with SUPERFEED™) is heavier
by 1.5 tons (confidence interval: 1.4–1.7 tons).”

⇒ **surplus information (test: zero included ?)**

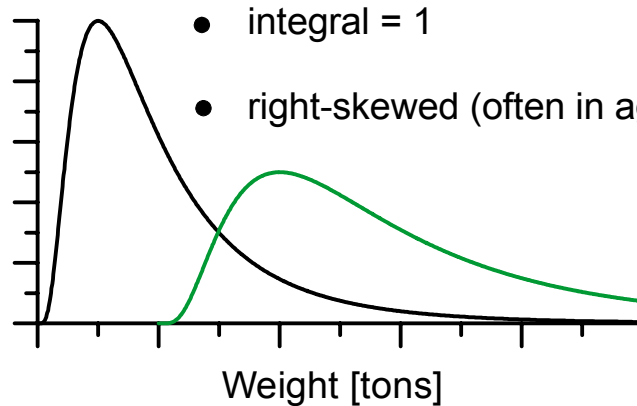


Statistics

“Cows with SUPERFEED™ have more weight than ordinary cows.”

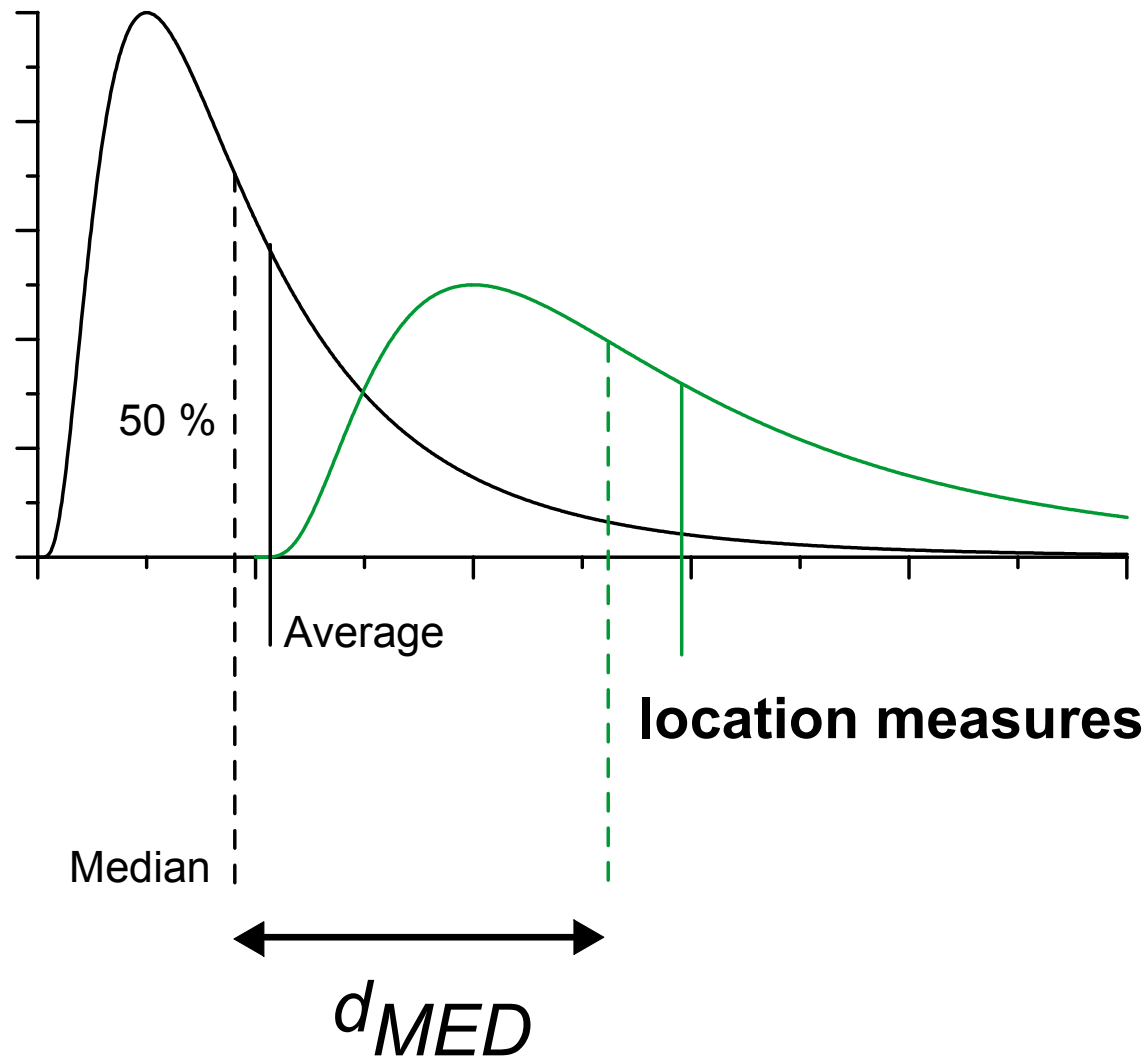
Probability density function
(population)

with SUPERFEED™
without SUPERFEED™



Probability density function
(population)

with SUPERFEED™
without SUPERFEED™



Estimation of population parameters with samples

n_1 cows with SUPERFEED™, weights $x_1(i), i = 1, \dots, n_1$
 n_2 cows without SUPERFEED™, weights $x_2(i), i = 1, \dots, n_2$

$$\begin{aligned} \widehat{d}_{MED} &= \text{sample median}\{x_1(1), \dots, x_1(n_1)\} - \\ &\quad \text{sample median}\{x_2(1), \dots, x_2(n_2)\} \\ &= 1.5 \text{ tons} \end{aligned}$$

“hat” notation

robust estimation:

only slightly affected by departures from assumptions

robust estimation:

only slightly affected by departures from assumptions

example normal assumption:

median = robust, mean = non-robust (large estimation error)

normal distribution:

Mean income in Giebichenstein = 700 EUR

median income = 700 EUR

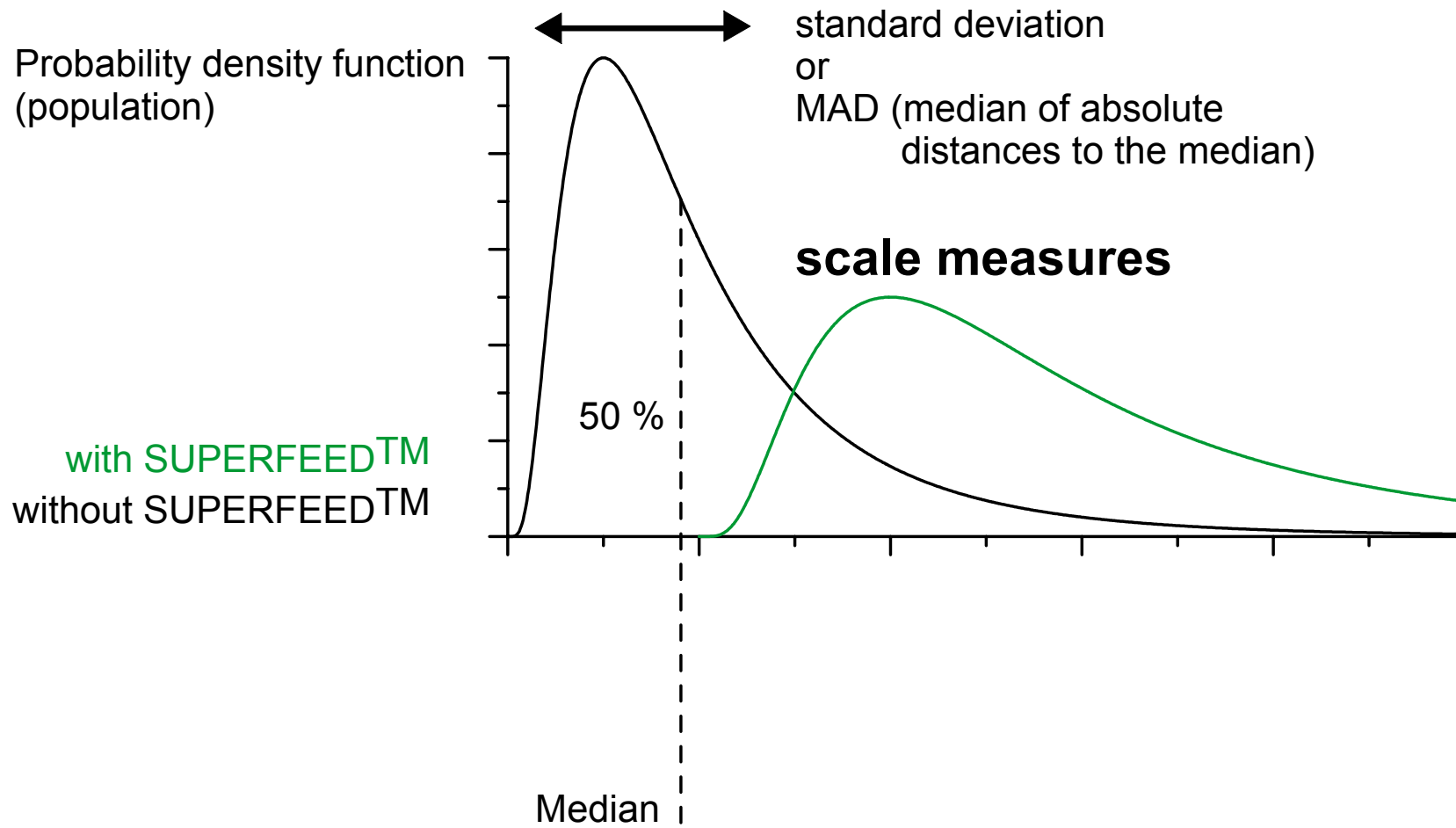
Michael Schumacher moves to Giebichenstein

⇒ right-skewed distribution

Mean income in Giebichenstein = 20000 EUR

median income = 700 EUR

Sample estimates—of mean but not of median—depend critically on whether or not Michael Schumacher is included.



	Treatment		Control	ν
Data	$x1$		$x2$	
Unpaired				
Size	$n1$		$n2$	
$\widehat{d_{AVE}}$	$= AVE(x1)$	$-$	$AVE(x2)$	$n1 + n2 - 2$
$\widehat{d_{MED}}$	$= MED(x1)$	$-$	$MED(x2)$	$n1 + n2 - 2$
$\widehat{d_{STD}}$	$= STD(x1)$	$-$	$STD(x2)$	$n1 + n2 - 4$
$\widehat{d_{MAD}}$	$= MAD'(x1)$	$-$	$MAD'(x2)$	$n1 + n2 - 4$

$AVE(x1) = \sum_{i=1}^{n1} x1(i)/n1 =$ sample mean,

$STD(x1) = \sqrt{\sum_{i=1}^{n1} \{x1(i) - AVE(x1)\}^2 / (n1 - 1)}$ = sample std,

$MED(x1)$ = sample median,

$MAD'(x1) = 1.4826MAD(x1)$,

$MAD(x1) = \text{median}\{|x1(i) - MED(x1)|\}$ = sample MAD

(normalizing: normal distribution has std = MAD');

analogously for $x2$;

ν = degrees of freedom

Unpaired experiment: independent samples

example: natural cows

Paired experiment: dependent samples, often: pairs

example: “cloned” cows (2 copies)

$x_1(1)$ = weight of 1st copy of cow 1
(with SUPERFEED™)

$x_2(1)$ = weight of 2nd copy of cow 1
(without SUPERFEED™)

$x_3(i) = x_1(i) - x_2(i)$

$\widehat{MED}_d = \text{sample median}\{x_3(i)\}$

advantage: inter-cow variability has no effect

	Treatment	Control	ν
Data	$x1$	$x2$	
Paired			
Size	$n1$	$=$	$n2$
\widehat{AVE}_d	$=$	$AVE(x1 - x2)$	$n1 - 1$
\widehat{MED}_d	$=$	$MED(x1 - x2)$	$n1 - 1$

$$AVE(x1 - x2) = \sum_{i=1}^{n1} \{x1(i) - x2(i)\} / n1,$$

$$MED(x1 - x2) = \text{median of } \{x3(i) = x1(i) - x2(i)\}, i = 1, \dots, n1$$

Note: measures of scale not of interest in paired experiment

Our aim: estimate confidence intervals for difference measures

$\widehat{d}_{AVE}, \widehat{d}_{MED}, \widehat{d}_{STD}, \widehat{d}_{MAD}$ **(unpaired)**

$\widehat{AVE}_d, \widehat{MED}_d$ **(paired)**

Problems: (partly) complicated measures

few data (5, 10)

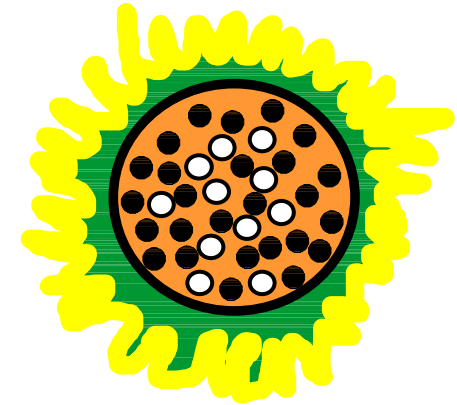
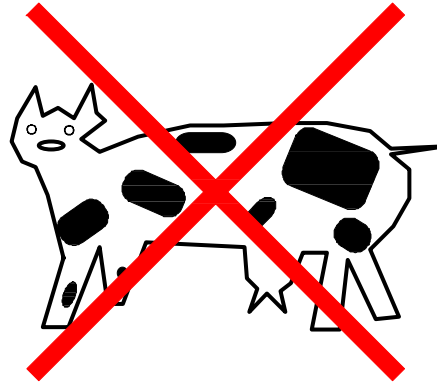
non-normal distributions

⇒ not much theory

Theory

Monte Carlo

Application



Mudelsee M, Alkio M (submitted) Bootstrap Confidence Intervals for Measures of Difference Between Two Samples: An Application to Sunflower Data. Journal of Agricultural, Biological, and Environmental Statistics.

<http://www.uni-leipzig.de/~meteo/MUDELSEE/talk/boottalk.pdf>

Bootstrap resampling

example

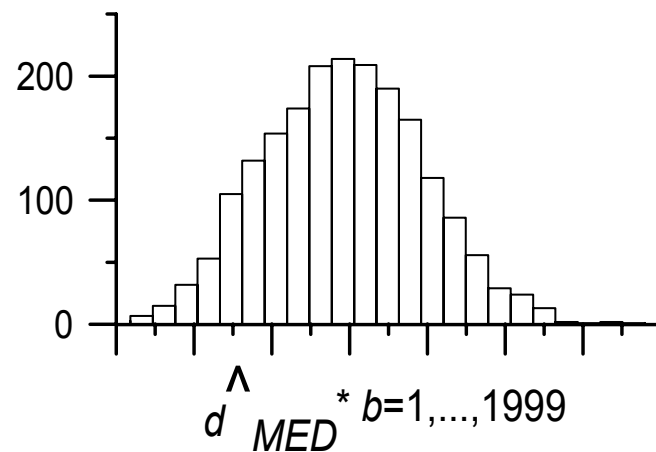
$$\begin{array}{ll}
 n1 = 4 & \{x1(1), x1(2), x1(3), x1(4)\} \\
 n2 = 3 & \{x2(1), x2(2), x2(3)\}
 \end{array}
 \quad d_{MED}^{\widehat{}}$$

resampling ($b = 1$) with replacement

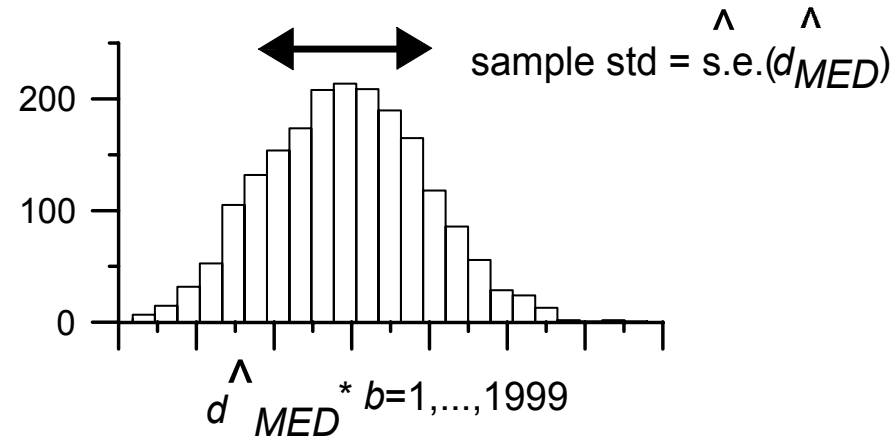
$$\begin{array}{ll}
 n1^* = 4 & \{x1^*(1), x1^*(2), x1^*(3), x1^*(4)\} \\
 & \{x1(3), x1(3), x1(4), x1(1)\} \\
 n2^* = 3 & \{x2^*(1), x2^*(2), x2^*(3)\} \\
 & \{x2(2), x2(3), x2(3)\}
 \end{array}
 \quad d_{MED}^{\widehat{*} \quad b=1}$$

Repeat B times in total (typically: $B \approx 2000$)

$\widehat{d}_{MED}^*_{b=1,\dots,B}$ bootstrap replications



Bootstrap idea: distribution of $\widehat{d}_{MED}^* \approx$ distribution of \widehat{d}_{MED}
(refinements account for differences)

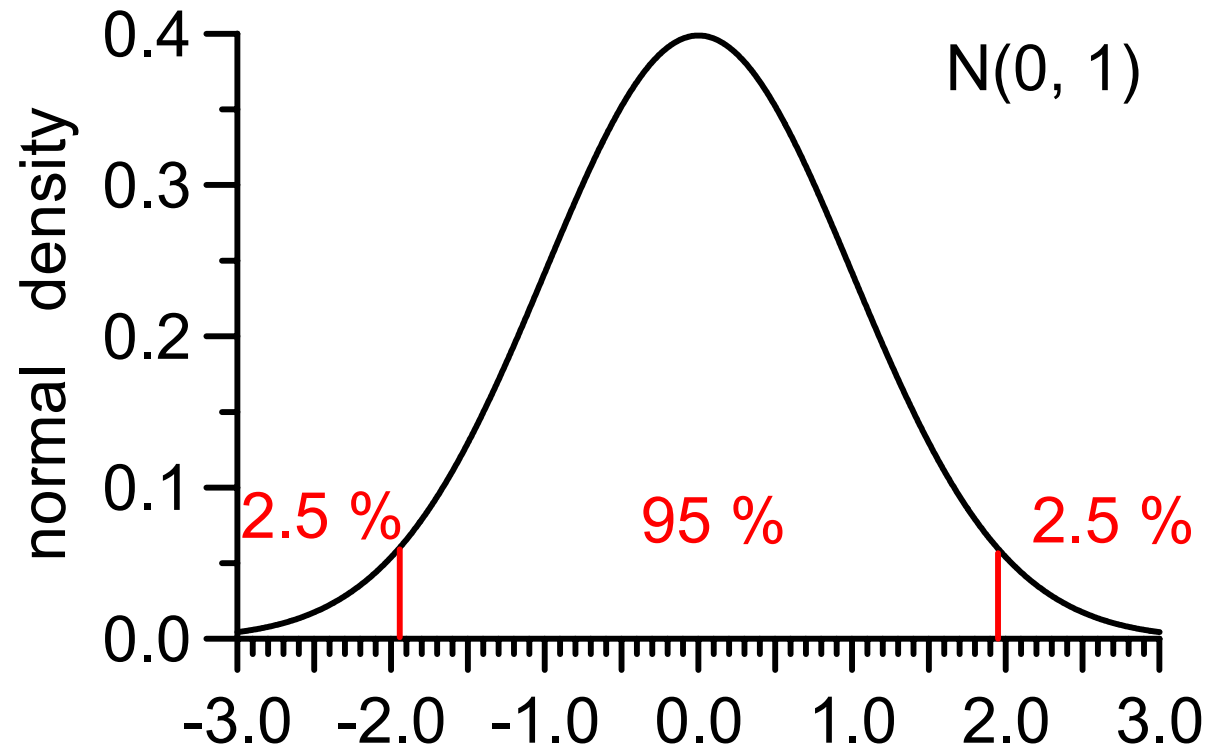


**

I Normal confidence interval

$$\left[\hat{d}_{MED} - z^{(1-\alpha)} \cdot \widehat{se} \left(\hat{d}_{MED} \right), \hat{d}_{MED} + z^{(1-\alpha)} \cdot \widehat{se} \left(\hat{d}_{MED} \right) \right]$$

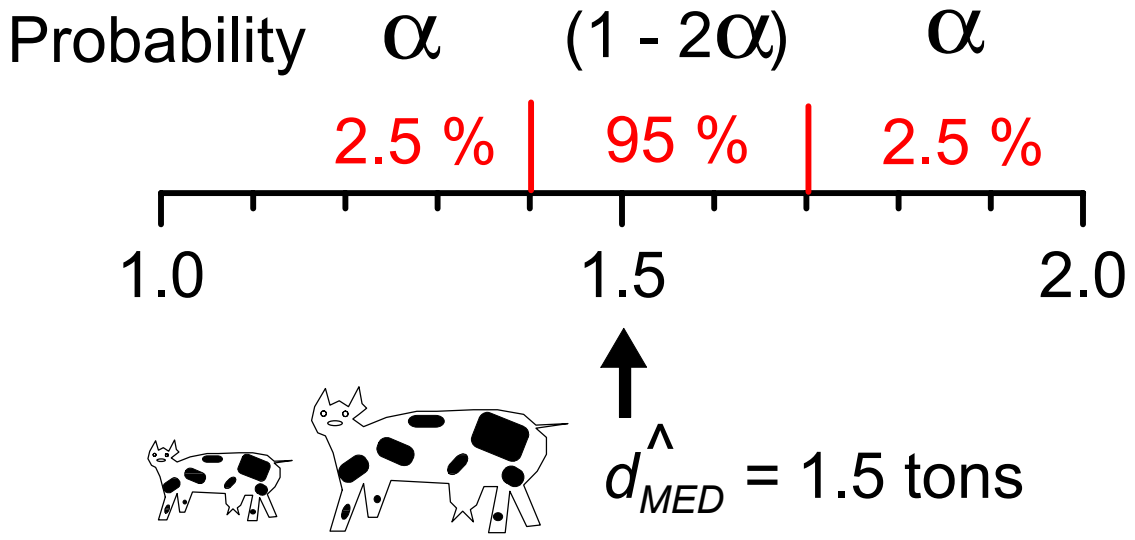
$z^{(1-\alpha)}$: standard normal percentile (e. g., $z^{(0.975)} = 1.96$) *



**

Confidence interval:

equi-tailed $(1 - 2\alpha)$ interval



II Student's t confidence interval

$$\left[\widehat{d}_{MED} - t_{\nu}^{(1-\alpha)} \cdot \widehat{se}(\widehat{d}_{MED}), \widehat{d}_{MED} + t_{\nu}^{(1-\alpha)} \cdot \widehat{se}(\widehat{d}_{MED}) \right]$$

$t_{\nu}^{(1-\alpha)}$: percentile Student's t distribution (ν degrees of freedom)

$\widehat{se}(\widehat{d}_{MED})$: unknown mean

\Rightarrow wider confidence interval than normal

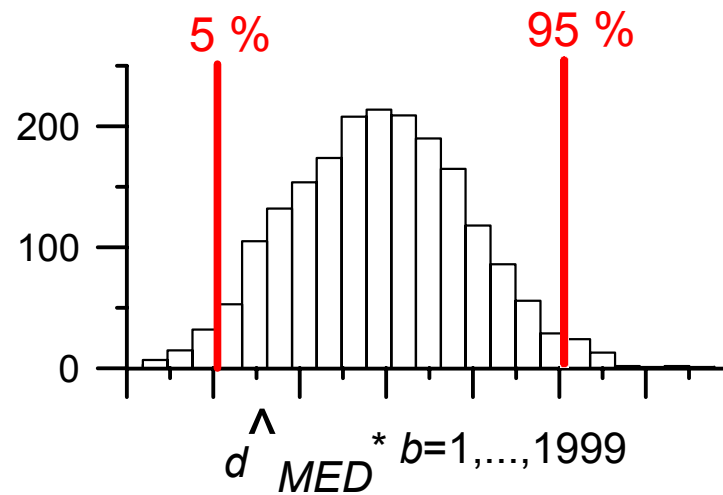
data sizes > 30 : differences negligible

Coverage error, C

Probability $\left[d_{MED} \leq \text{lower confidence bound for } d_{\widehat{MED}} \right] = \alpha + C$

terms of $C \propto 1/\sqrt{n}$ and “faster”: first -order accurate

terms of $C \propto 1/n$ and “faster”: second-order accurate

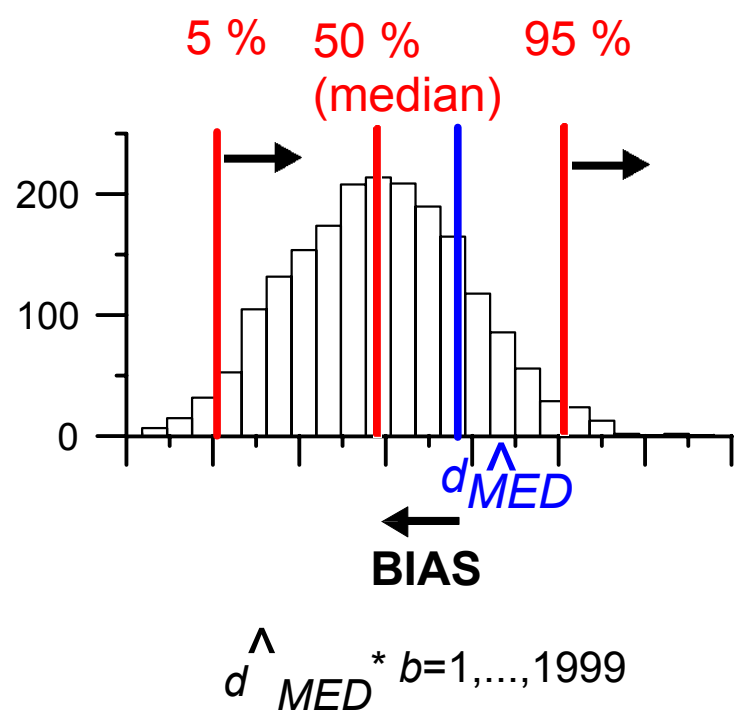


III Percentile confidence interval

$$\left[d_{MED}^* \widehat{b=1, \dots, B=\infty}(\alpha), d_{MED}^* \widehat{b=1, \dots, B=\infty}(1-\alpha) \right]$$

practice ($B < \infty$): approximate interval

example: $B = 1999$, 95th percentile = $0.95 \cdot (1999 + 1)$ th
 = 1900th largest d_{MED}^* value



IV BCa confidence interval

bias correction \hat{z}_0

“acceleration” \hat{a} : ($\widehat{s.e.}(d_{MED}^{\wedge})$) needs not to be constant)
rate of change of $\widehat{s.e.}(d_{MED}^{\wedge})$ with d_{MED}

BCa interval: $\left[\widehat{d}_{MED}^{*b=1, \dots, B=\infty} (\alpha 1), \widehat{d}_{MED}^{*b=1, \dots, B=\infty} (\alpha 2) \right]$

$$\alpha 1 = \Phi \left[\widehat{z}_0 + \frac{\widehat{z}_0 + z(\alpha)}{1 - \widehat{a} (\widehat{z}_0 + z(\alpha))} \right],$$

$$\alpha 2 = \Phi \left[\widehat{z}_0 + \frac{\widehat{z}_0 + z(1-\alpha)}{1 - \widehat{a} (\widehat{z}_0 + z(1-\alpha))} \right],$$

$$\widehat{z}_0 = \Phi^{-1} \left(\frac{\text{number of replications where } \widehat{d}_{MED}^{*b} < \widehat{d}_{MED}}{B} \right), \quad [\text{Note: } \Phi^{-1}(1/2) = 0]$$

$$\widehat{a} = \frac{\sum_{i=1}^{n1} \sum_{j=1}^{n2} \left(\langle \widehat{d}_{MED\text{jack}(i, j)} \rangle - \widehat{d}_{MED\text{jack}(i, j)} \right)^3}{6 \left[\sum_{i=1}^{n1} \sum_{j=1}^{n2} \left(\langle \widehat{d}_{MED\text{jack}(i, j)} \rangle - \widehat{d}_{MED\text{jack}(i, j)} \right)^2 \right]^{3/2}}.$$

Theory

standard-error based

accuracy (order)

I Normal confidence interval

1st [estimator \sim normal: 2nd]

II Student's t confidence interval

1st [estimator \sim normal: 2nd]

percentile-based

III Percentile confidence interval

1st

IV BCa confidence interval

2nd

Why all that stuff ???

Treatment and control populations: in general non-normal
⇒ no “normal” theory

small data sizes
⇒ no asymptotic theory

d_{MED} , d_{MAD} , MED_d : order statistics
⇒ analytical derivations difficult/impossible

Why not use transformations of data to normality ???

- Idea: use of something like $\sqrt{STD(x1)^2/n1 + STD(x2)^2/n2}$ (normal theory) for calculating confidence intervals
- But: Can be laborious if many data sets are to be analyzed.
- But: This method needs not provide the same information. *

*

	$x1$	$x2$	data
	$x1' = g_1(x1)$	$x2' = g_2(x2)$	transformation
	$x1' = \log(x1)$	$x2' = \log(x2)$	example
d'_{MED}	$= MED(x1') -$	$MED(x2')$	
	$= MED[\log(x1)] -$	$MED[\log(x2)]$	
	$= \log[MED(x1)] -$	$\log[MED(x2)]$	log = monotonic
	$= \log \left[\frac{MED(x1)}{MED(x2)} \right]$		

d'_{MED} offers information about **ratio** of original medians (not about difference)

g_1, g_2 different and/or more complex: d'_{MED} difficult to interpret

Notes

- Further types of bootstrap confidence intervals, “double bootstrap”, bootstrap calibration etc. \Rightarrow computationally more expensive
- bootstrap: becoming standard method in Statistics, current research: (e. g.) confidence intervals
- bootstrap: seen from time to time in Physics, Geosciences, has been seen in Agriculture

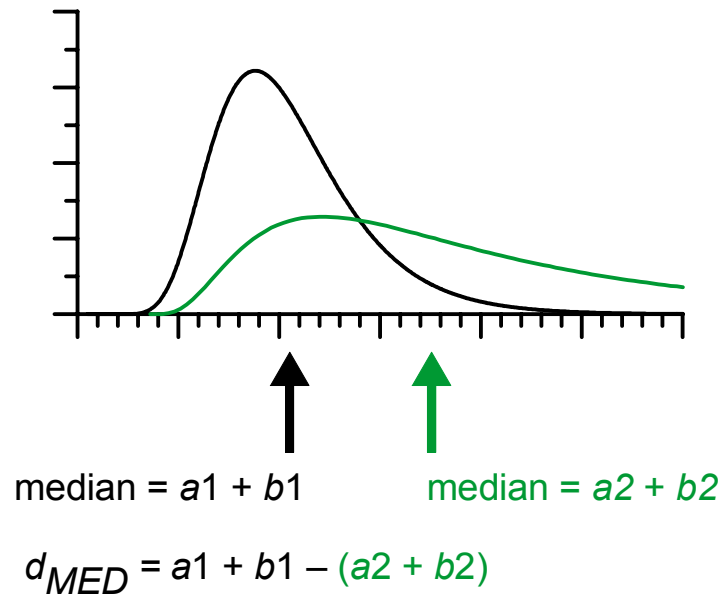
Reading:

- Efron B (1979) Bootstrap methods: Another look at the jackknife. The Annals of Statistics 7:1–26. [introduces bootstrap]
- Efron B, Tibshirani RJ (1993) An Introduction to the Bootstrap. Chapman & Hall, London, pp 436. [accessible textbook]
- Hall P (1988) Theoretical comparison of bootstrap confidence intervals (with discussion). The Annals of Statistics 16:927–985. [calculates coverage errors]

Lognormal treatment and control

$$f1(x) = \frac{1}{s1(x-a1)} \frac{1}{\sqrt{2\pi}} \exp \left[-\frac{1}{2s1^2} \left[\ln \left(\frac{x-a1}{b1} \right) \right]^2 \right] = \text{LN}(a1, b1, s1)$$

$$f2(x) = \text{LN}(a2, b2, s2)$$



Draw random sample $x_1 \sim \text{LN}(a_1, b_1, s_1)$, size n_1

Draw random sample $x_2 \sim \text{LN}(a_2, b_2, s_2)$, size n_2

Correlation: ρ_{LN}

Calculate Bootstrap confidence interval $(1 - 2\alpha)$ for \widehat{d}_{MED}

Count: $d_{\text{MED}} <$ lower bound of confidence interval (nominal: $P = \alpha$)

$d_{\text{MED}} \in$ confidence interval (nominal: $P = 1 - 2\alpha$)

$d_{\text{MED}} >$ upper bound of confidence interval (nominal: $P = \alpha$)

Repeat procedure: 10000 Monte Carlo simulations

Compare empirical with nominal coverages

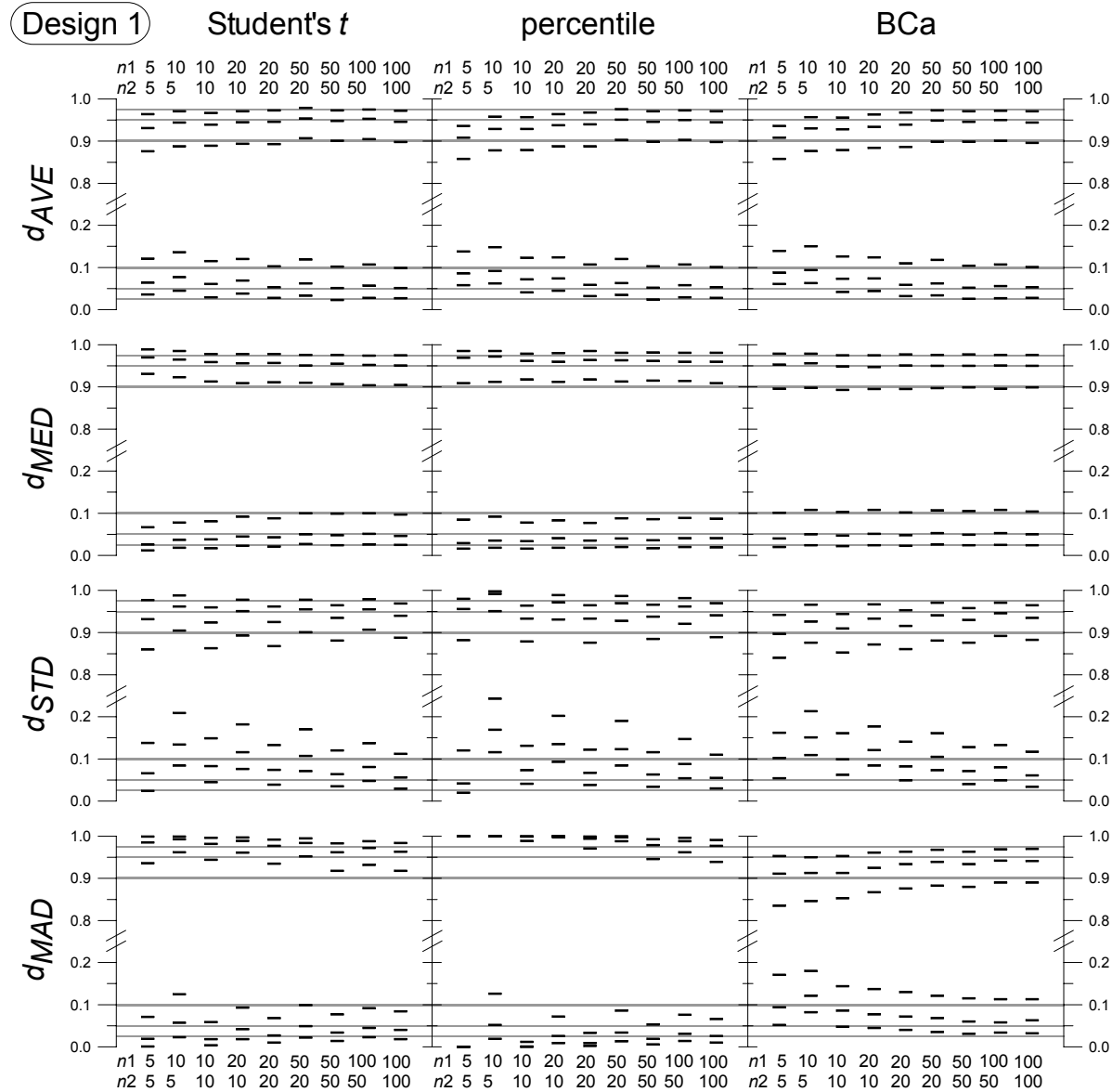
Monte Carlo

Monte Carlo Designs; Lognormal Parameters and Theoretical Difference Measures

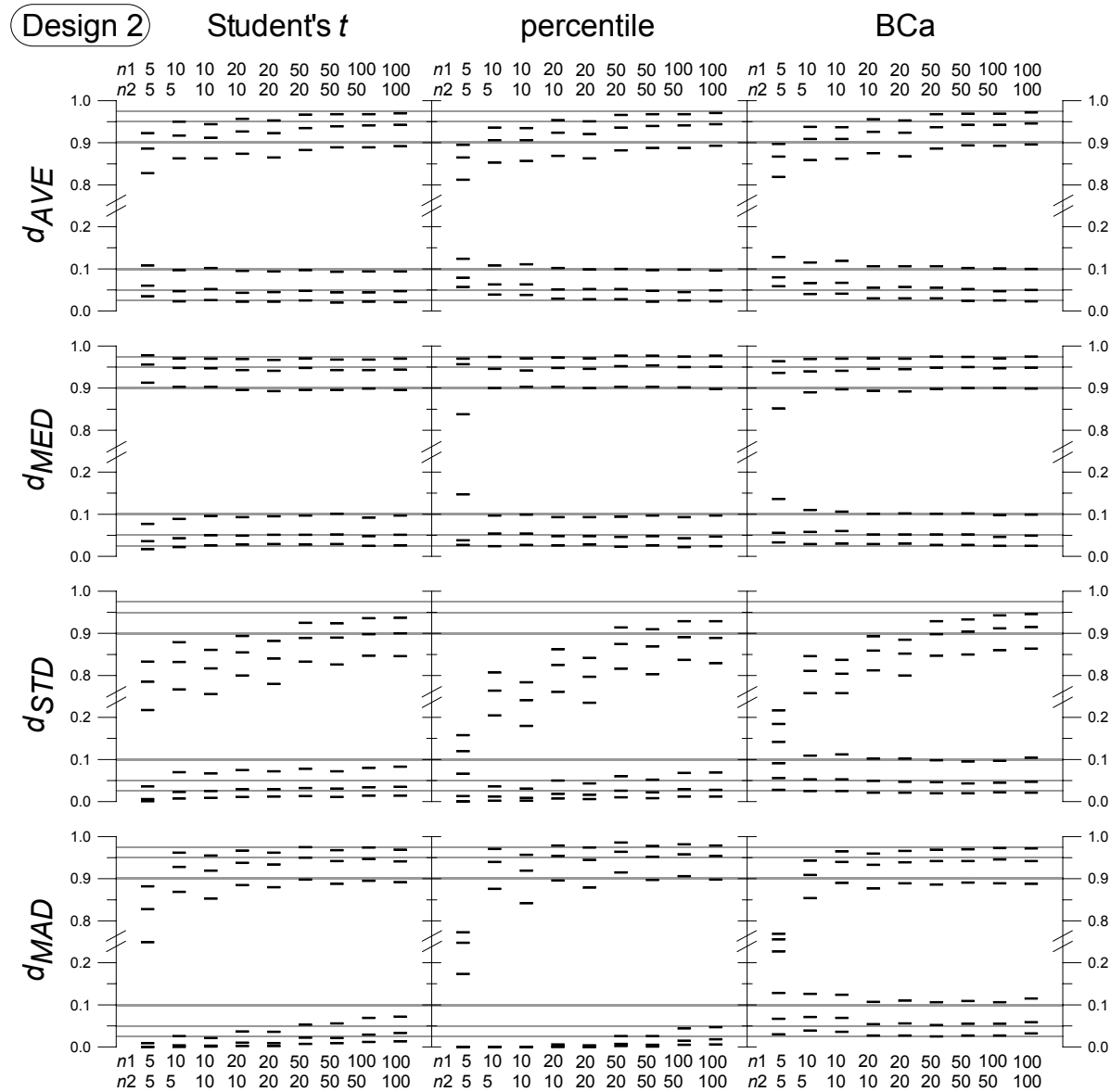
Design	$a1$	$b1$	$s1$	$a2$	$b2$	$s2$	d_{AVE}	d_{MED}	d_{STD}	d_{MAD}	MED_d
1	0	4	.2	0	4	.2	0	0	0	0	0
2	0	25.3	.2	0	4	.2	21.73	21.30	4.39	4.24	21.24
3	0	4	.8	0	4	.2	1.43	0	4.39	2.17	0
4	0	25.3	.8	0	25.3	.8	0	0	0	0	0

NOTES: $AVE_d = d_{AVE}$, MED_d determined by preliminary simulation

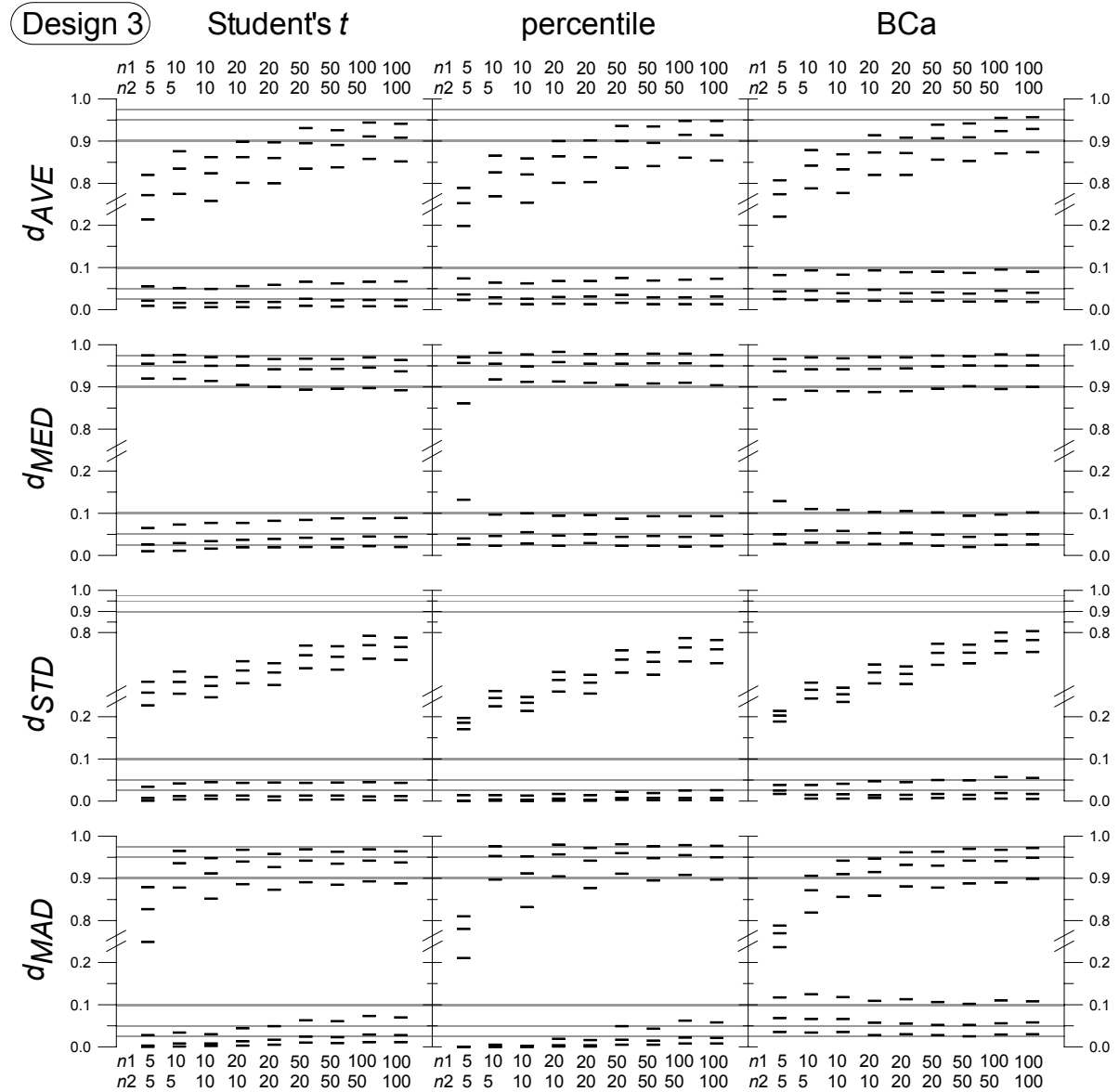
$\rho_{LN} = 0$ (correctly specified unpaired)



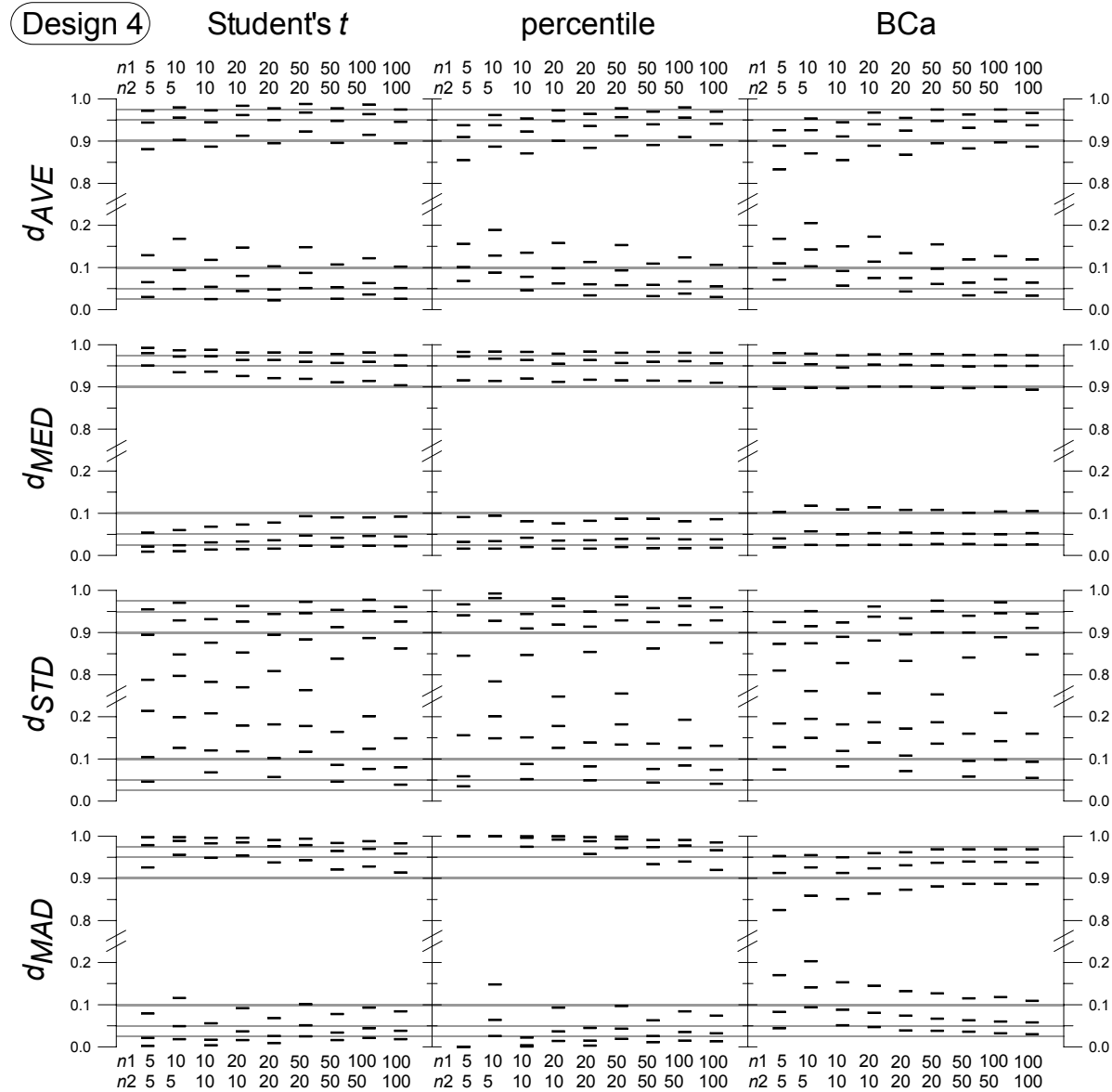
$\rho_{LN} = 0$ (correctly specified unpaired)



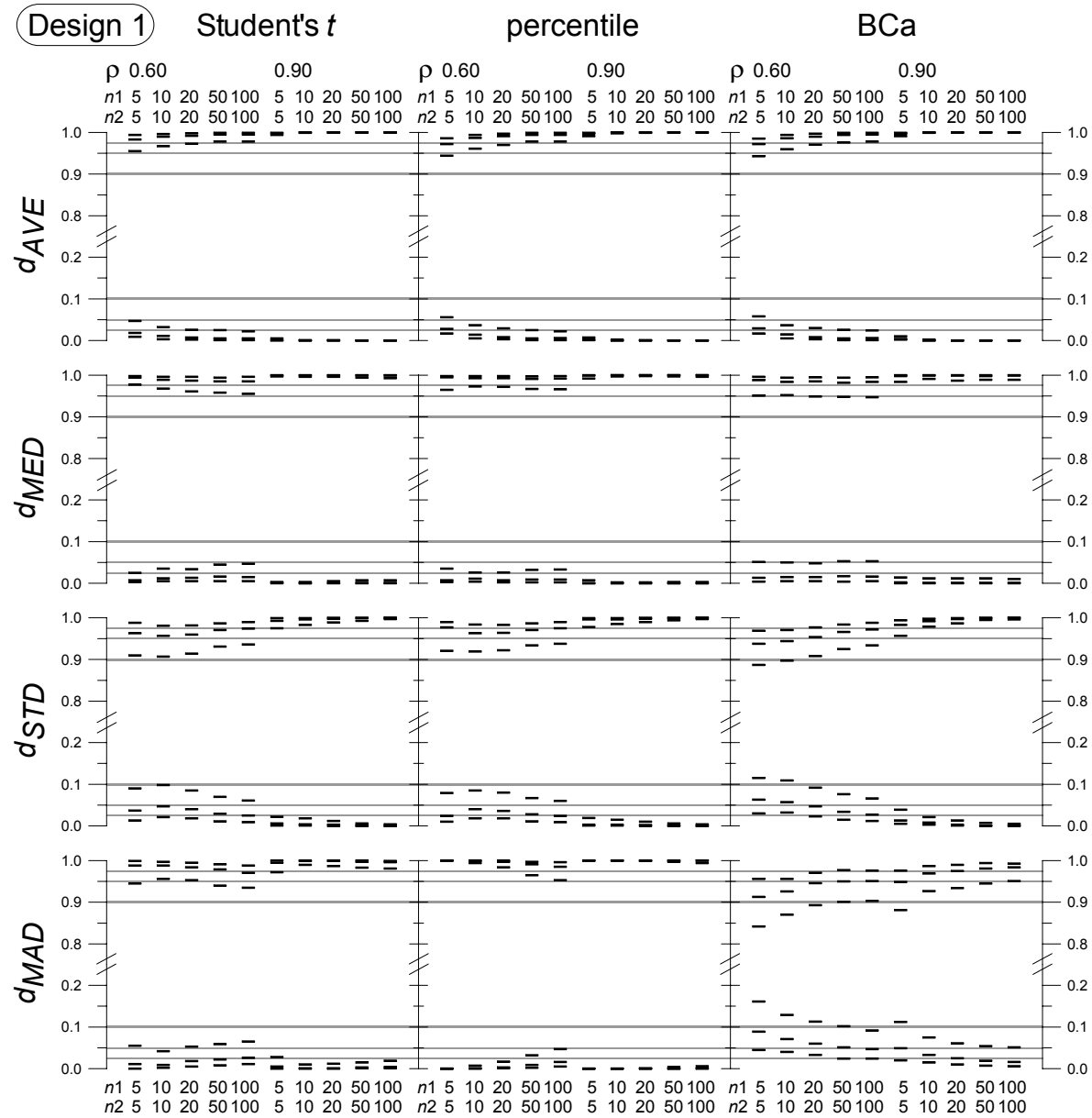
$\rho_{LN} = 0$ (correctly specified unpaired)



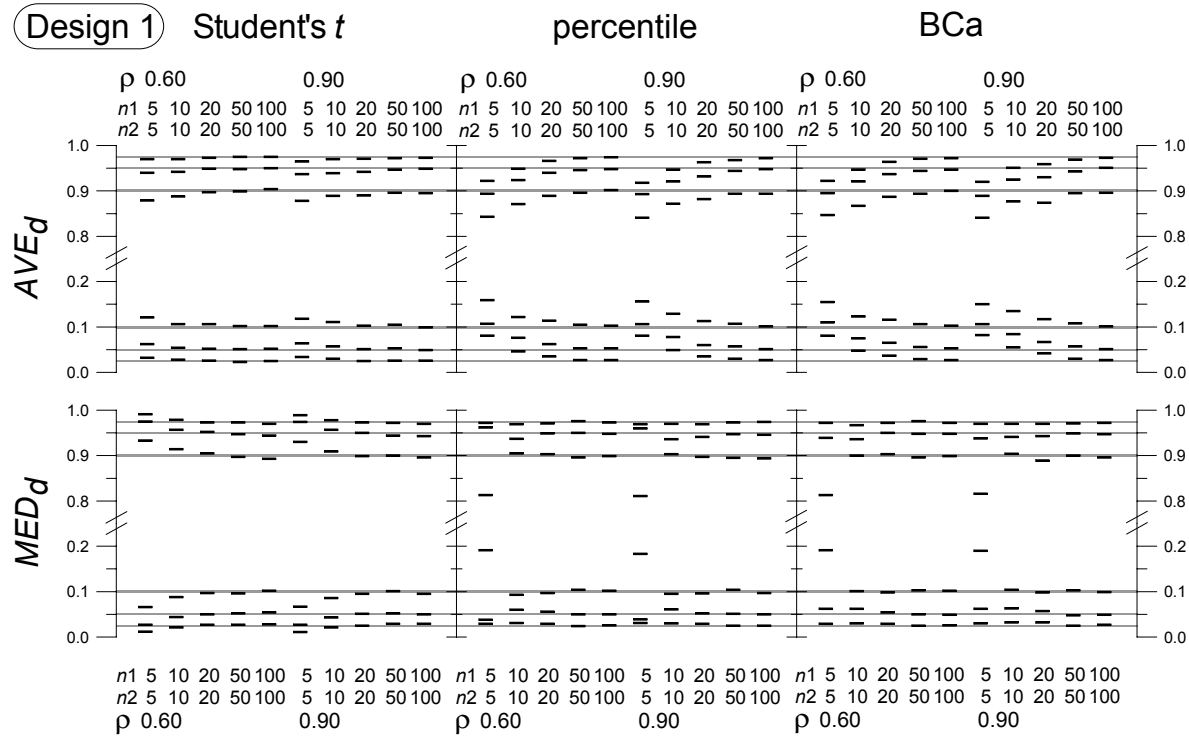
$\rho_{LN} = 0$ (correctly specified unpaired)



$\rho_{LN} \neq 0$ (mis-specified unpaired)



$\rho_{LN} \neq 0$ (correctly specified paired)



Result

- **BCa** and **Student's t** confidence intervals of \widehat{MED}_d as measure of location of difference offer good coverage performance in **paired** experiments for $n_1 \gtrsim 10$ and $n_2 \gtrsim 10$.
- **BCa** confidence intervals of \widehat{d}_{MED} as measure of difference in location offer good coverage performance in **unpaired** experiments for $n_1 \gtrsim 20$ and $n_2 \gtrsim 20$.
- **BCa** confidence intervals of \widehat{d}_{MAD} as measure of difference in scale offer acceptably coverage performance in **unpaired** experiments for $n_1 \gtrsim 50$ and $n_2 \gtrsim 50$.

Application

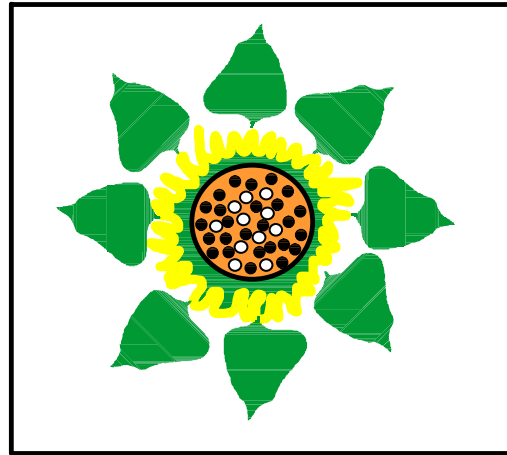
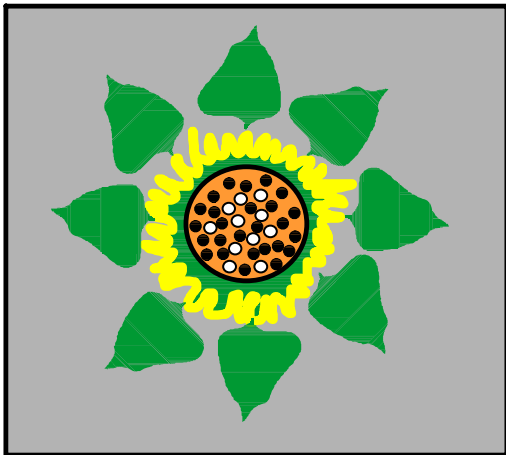
Helianthus annuus L. — source–sink ratio manipulations

x = percentage of unfilled achenes

shading

ratio \uparrow

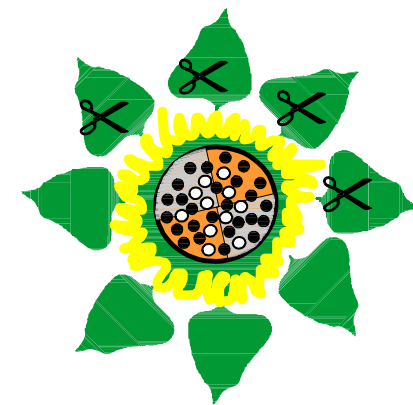
unpaired experiment



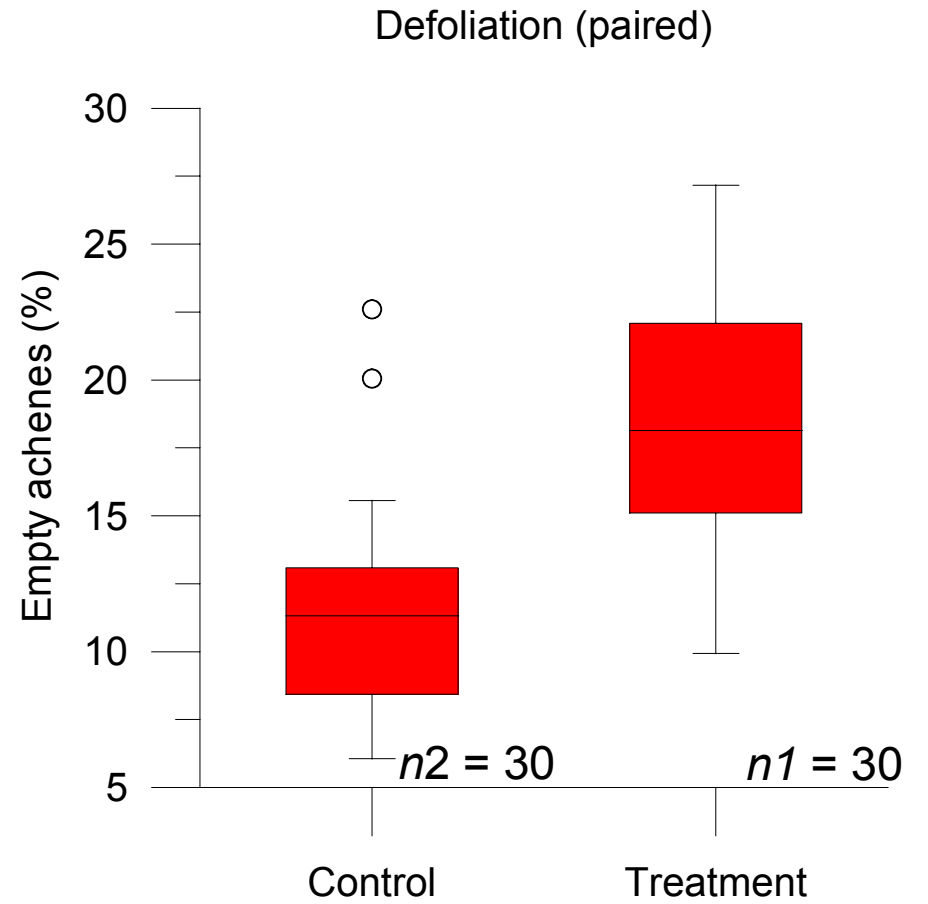
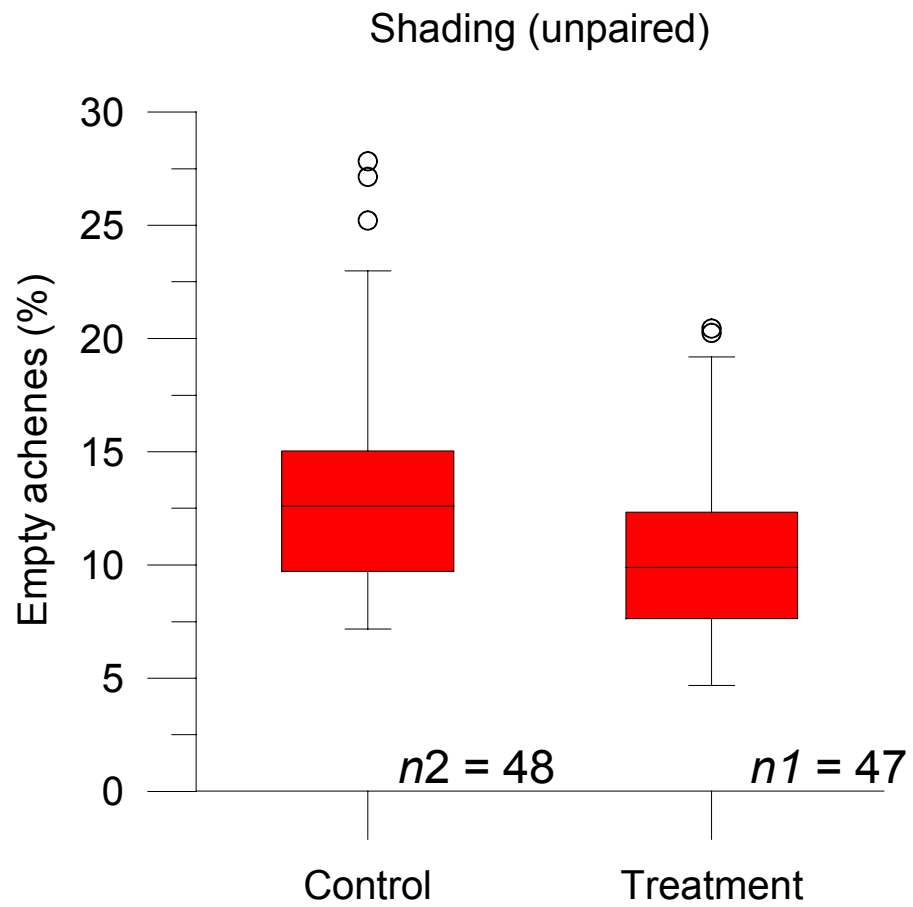
defoliation

ratio \downarrow

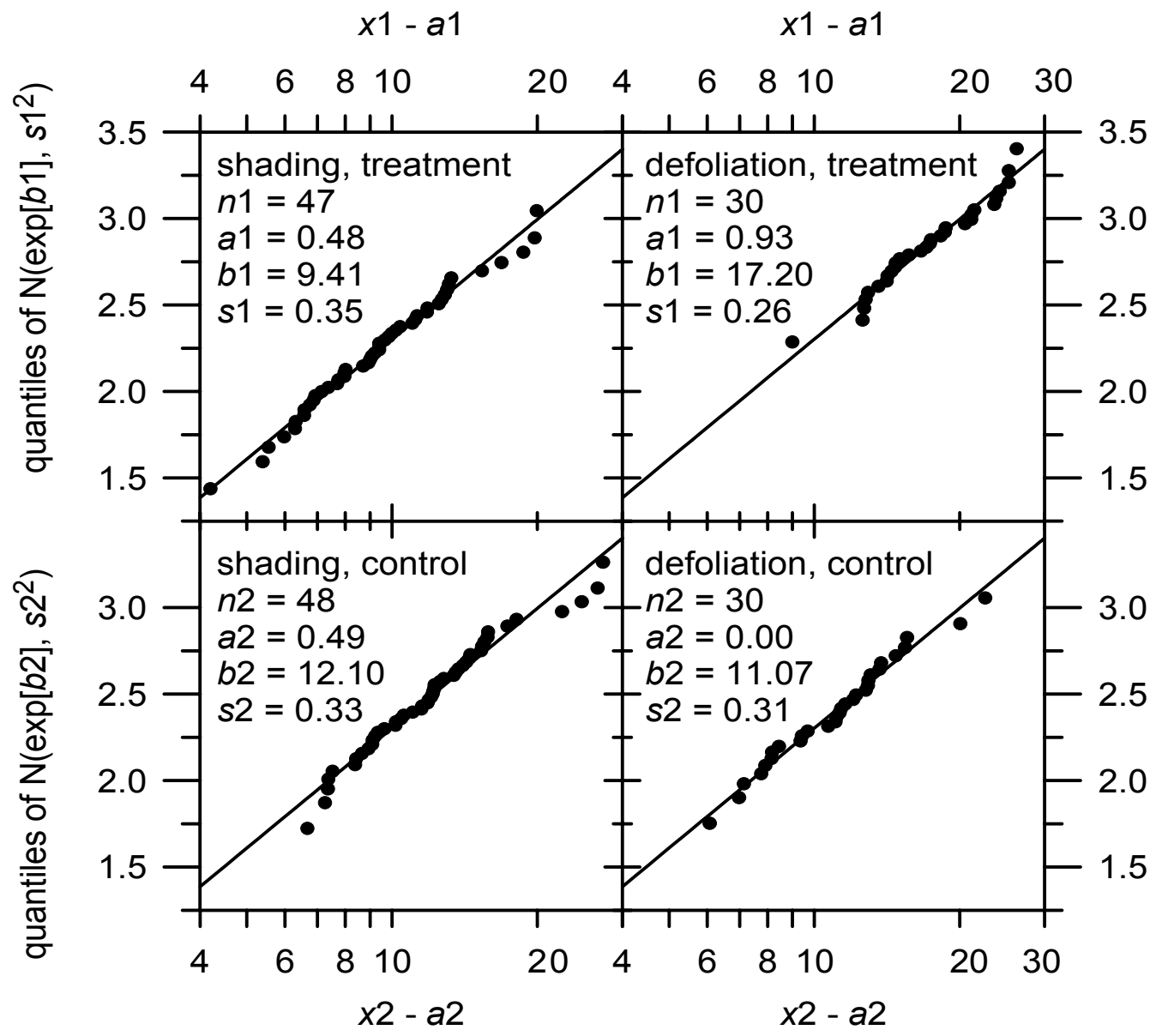
paired experiment



Application



Application



2SAMPLES demonstration

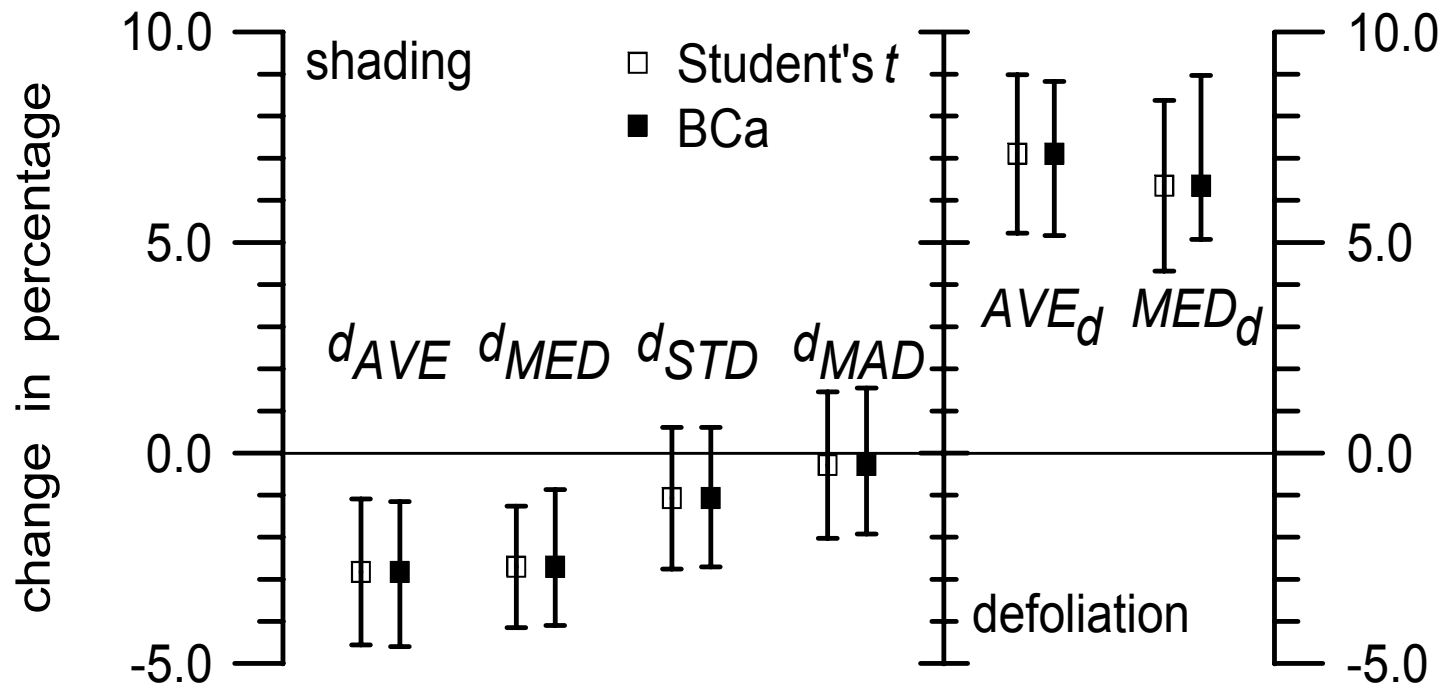
f:\2samples\data\u_p__123.t

f:\2samples\data\u_p__123.k

f:\2samples\data\p_p__1_6.t

f:\2samples\data\p_p__1_6.k

Final result



Bootstrap confidence intervals

- works for relatively small data sizes
- works for non-normal distributions
- works also for complicated measures
- avoids transformations
- **surplus information (test: zero included ?)**