

Medicine, Nursing and Health Sciences

Challenges with continuous outcomes (part A)

Jo McKenzie (joanne.mckenzie@monash.edu) Cochrane Methods Training Event 2016 Birmingham, UK, 17-18th March 2016

Session plan

1. Combining estimates from analyses of final values, change scores, and ANCOVA

Practical (group discussion)

2. Meta-analysis of skewed data

Practical (computer)

3. Ratio of arithmetic means

Practical (computer)



Effect measures for continuous outcomes

Effect measure	
Difference effect measures	
Mean difference	$MD = \bar{Y}_{int} - \bar{Y}_{ctrl}$
Standardised mean difference	$SMD = \left(rac{\overline{Y}_{int} - \overline{Y}_{ctrl}}{S_{pooled}} ight)$
Ratio effect measures	
Ratio of means	$RoM = \frac{\overline{Y}_{int}}{\overline{Y}_{ctrl}}$
Ratio of geometric means	$RoGM = \frac{G_{int}}{G_{ctrl}}$



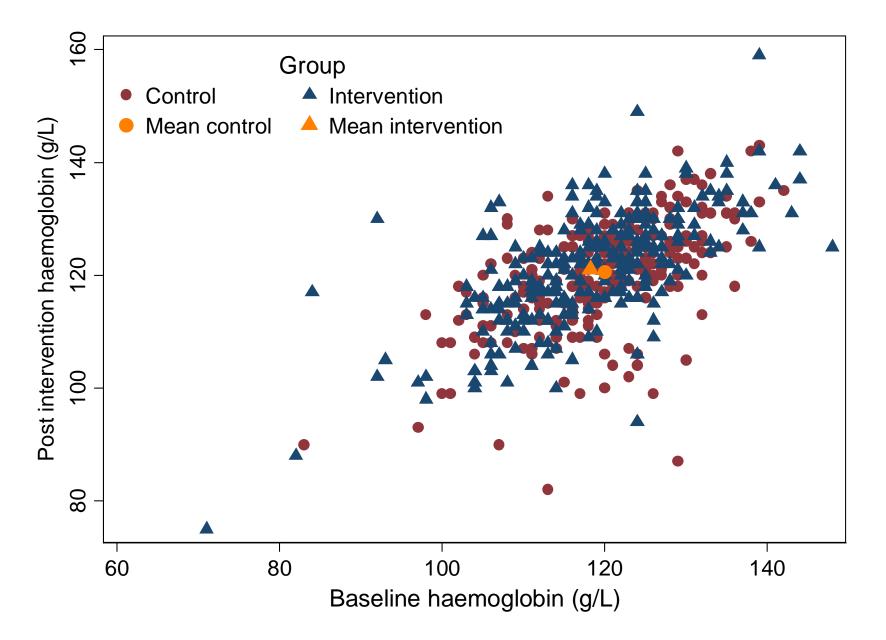
Combining estimates from analyses of final values, change scores, and ANCOVA



Analysis of a randomised trial with measurements before and after intervention

- Randomised trial carried out in the Ubon Ratchathani province NE Thailand
- Aimed to test the efficacy of a seasoning powder fortified with micronutrients
- Groups:
 - Intervention: fortified seasoning powder added to instant wheat noodles or rice
 - Control: unfortified seasoning powder added to instant wheat noodles or rice
- Data collected at baseline and follow-up (31 weeks)
- Primary outcome was anaemia (defined from the continuous variable haemoglobin)

Post intervention haemoglobin vs baseline haemoglobin



Analysis options

 Ignore the baseline values, and calculate the difference in means at follow-up between groups (simple analysis of final values SAFV)

$$\hat{\theta}_{SAFV} = \bar{Y}_{int} - \bar{Y}_{ctrl}$$

• Adjust for baseline by calculating the difference in mean change (Y - X) between groups (simple analysis of change scores SACS)

$$\hat{\theta}_{SACS} = (\bar{Y}_{int} - \bar{Y}_{ctrl}) - (\bar{X}_{int} - \bar{X}_{ctrl})$$

Adjust for baseline using regression modelling (ANCOVA)

$$\hat{\theta}_{ANCOVA} = (\bar{Y}_{int} - \bar{Y}_{ctrl}) - \hat{\beta}(\bar{X}_{int} - \bar{X}_{ctrl})$$

where $\beta = \rho \frac{\sigma_Y}{\sigma_X}$ and is estimated from the regression model

MONASH University

Data sets used to illustrate the impact of correlation on intervention effect estimates

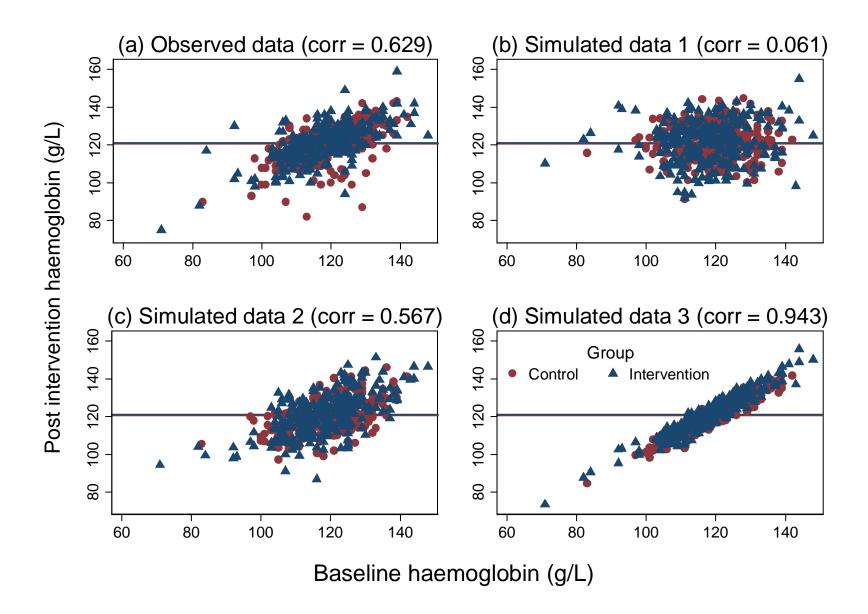
Dataset	Observed correlation	Follow-up haemoglobin (g/L)					
		Interv	ention group	Cor	ntrol group		
		Mean	SD	Mean	SD		
Observed data	0.629	121.0	10.1	120.5	9.5		

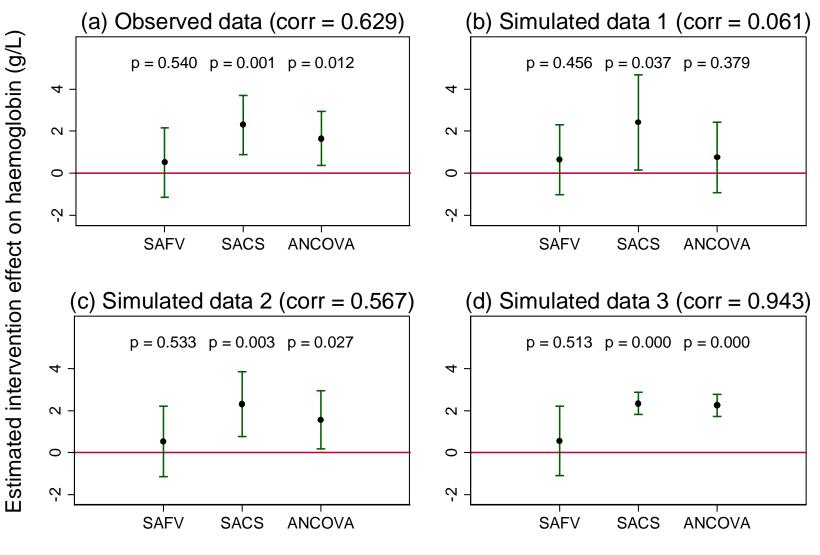


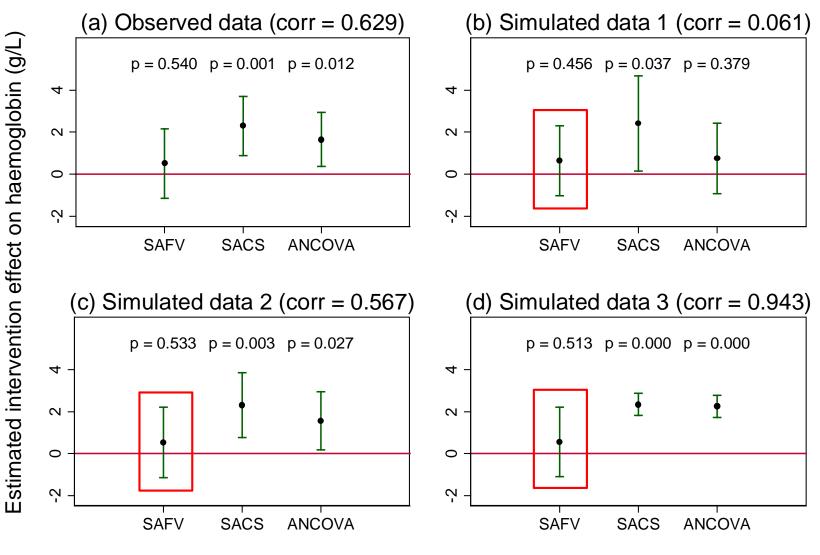
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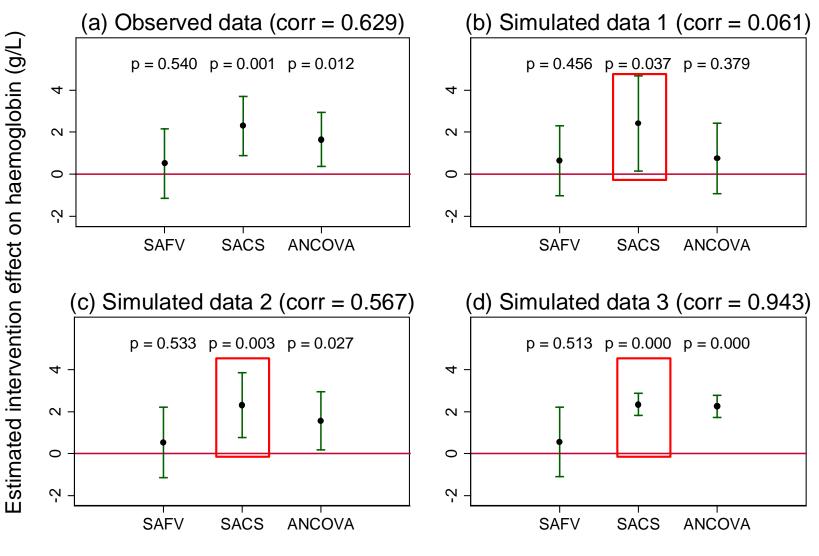
Dataset	Observed correlation	Follow-up haemoglobin (g/L)					
		Interv	ention group	Cor	ntrol group		
		Mean	SD	Mean	SD		
Observed data	0.629	121.0	10.1	120.5	9.5		
Simulated data 1	0.061	121.2	10.8	120.6	8.8		
Simulated data 2	0.567	121.2	10.8	120.6	8.8		
Simulated data 3	0.943	121.1	10.5	120.5	9.0		

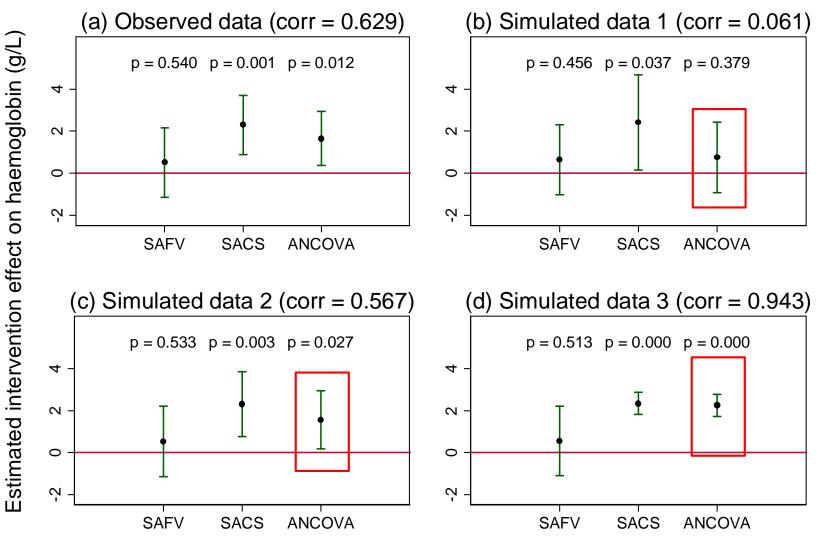
Scatter plots of post intervention haemoglobin vs baseline haemoglobin for observed and simulated data sets











Comparing the trial analysis methods

- Estimates of intervention effect:
 - For a particular data set, the three analytical methods can produce different estimates of intervention effect
 - Over the data sets (varying correlation), the ANCOVA estimate varies;
 SACS or SAFV estimates do not
- Standard errors:
 - The SE of the SAFV estimate is not affected by correlation
 - Increasing correlation results in a smaller SE for the SACS estimate
 - Correlation < 0.5, the SE of SACS estimate is > SE of the FV estimate.
 This is reversed when the correlation is > 0.5
 - For a particular correlation, the SE of the ANCOVA estimate is smaller compared with SEs of FV and CS estimates

Relationship between the three analysis methods

$$\hat{\theta}_{ANCOVA} = (\bar{Y}_{int} - \bar{Y}_{ctrl}) - \rho(\bar{X}_{int} - \bar{X}_{ctrl})$$
(assuming $\sigma_Y^2 = \sigma_X^2$)

Scenario 1: ρ is close to 0

 $\hat{\theta}_{ANCOVA} \approx \hat{\theta}_{SAFV}$

Scenario 2: ρ is close to 1

$$\hat{\theta}_{ANCOVA} \approx \hat{\theta}_{SACS}$$

• Scenario 3: minimal baseline imbalance, i.e. $(\bar{X}_{int} - \bar{X}_{ctrl}) \approx 0$ $\hat{\theta}_{ANCOVA} \approx \hat{\theta}_{SACS} \approx \hat{\theta}_{SAFV}$

Practical (group discussion)



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When undertaking a systematic review ...

- Likely to encounter estimates calculated from different analysis methods
- This could include:
 - SACS
 - SAFV
 - Sometimes SACS and SAFV
 - Sometimes ANCOVA
- Practical: Discussion of a meta-analysis from a systematic review examining the effect of calcium supplementation on body weight (Trowman 2006 Br J Nut)



Study characteristics (modified table 1) (Trowman 2006 Br J Nut)

Study	Number of participants	Age*	Sex	Intervention (Ca concentration)	Length of follow-up	Country
Chee et al. (2003)	173	58-9	Female (postmenopausal)	Ca supplement (1200 mg/d)	24 months	Malaysia
Jensen et al. (2001)	52	NA	Female (obese postmenopausal)	Ca supplement (1000 mg/d)	26 weeks	Denmark
Lau et al. (2001)	185	57.0	Female (postmenopausal)	Ca supplement (800 mg/d)	24 months	China
Reid et al. (2002)	223	72.0	Female (postmenopausal)	Ca supplement (1000 mg/d)	24 months	New Zealand
Shapses et al. (2004)	36	59.3	Female (obese postmenopausal)	Ca supplement (1000 mg/d)	25 weeks	USA
Shapses et al. (2004)	30	56-0	Female (obese postmenopausal)	Ca supplement (1000 mg/d)	25 weeks	USA
Shapses et al. (2004)	42	41.0	Female (obese postmenopausal)	Ca supplement (1000 mg/d)	25 weeks	USA
Winters-Stone & Snow (2004)	23	24.8	Female (athletes)	Ca supplement (1000 mg/d)	12 months	USA
Zemel et al. (2004)	41	46	Mixed (obese)	Calcium supplement (800 mg/d)	24 weeks	USA

NA, not available

* Mean age. When age was reported separately by subgroups, the mean between the groups was calculated.

Calcium supplementation on body weight (Trowman 2006 Br J Nut)

Trial	Year	Baseline (weight kg)				Follow-up (we	eight kg)	Change (we	eight kg)
		Int	tervention		Control	Intervention	Control	Intervention	Control
		N	Mean (SD)	n	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)
Chee	2003	91	56.1 (8.9)	82	57.2 (9.4)			0.0 (2.6) ^a	0.2 (2.6) ^a
Jensen	2001	25	94.6 (14.0) ^a	27	93.8 (14.0) ^a	89.0 (12.7) ^a	89.1 (14.7) ^a		
Lau	2001	95	56.9 (7.1)	90	58.9 (7.5)			0.5 (2.6)ª	-0.3 (2.7) ^a
Reid	2002	111	66.0 (10.0)	112	68.0 (11.0)			-0.3 (1.8)	-0.1 (2.4)
Shapses 1°	2004	17	84.1 (9.4)	19	89.4 (10.3)			-7.0 (4.6)	-7.3 (5.3)
Shapses 2 ^c	2004	11	85.9 (9.2)	11	94.2 (15.7)			-6.7 (2.6)	-7.6 (5.7)
Shapses 3°	2004	18	93.7 (13.6)	24	93.5 (14.3)			-6.7 (5.5)	-4.3 (3.5)
Winters-Stone	2004	13	57.2 (4.9)	10	54.1 (7.2)	56.3 (4.3)	54.8 (7.2)		
Zemel	2004	11	99.8 (14.9)	10	103.1 (19.3)			-8.6 (5.3) ^a	-6.6 (8.2) ^a

a Calculated from the standard error

b Follow-up sample size ntrt = 24 and nctrl = 24

c Shapses et al (Shapses et al, 2004) report on three randomised controlled trials.

Trials 1, 2, and 3 include postmenopausal women, postmenopausal women special diet, and premenopausal women respectively.

Practical

- How would you undertake a meta-analysis of this data?
 - What data would you choose, and why?
 - Would you impute any data, and how?



Option	Advantages	Disadvantages
1) Individual patient data: Obtain IPD for each trial. Reanalyse using conventional two-step approach, or a more complex approach such as multilevel modelling. ANCOVA would be the method of choice within each trial	 Avoids the issue of trialists selectively reporting results Able to re-analyse data in a consistent way Potentially adjust for other prognostic factors Can use the most powerful analytical method Do not have to rely on summary data provided in publications 	• Generally not possible to obtain IPD



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2) Meta-analysis using only ANCOVA results: Use available ANCOVA estimates. When not available, recreate the estimates from available summary statistics, or imputing missing statistics (e.g. correlations)	 Reduce bias from random baseline imbalance across the included randomised trials or from selective reporting of results May provide greater precision compared with pooling results from SAFV or SACS 	 Will generally require assumptions to be made regarding the correlation Will require data manipulation

Option	Advantages	Disadvantages
3) Meta-analysis using results from only one analysis method (SAFV or SACS): Meta-analyse estimates using the same analysis method. This approach may involve imputing missing statistics (e.g. correlations)	 Removes bias from trialists selectively reporting analyses 	 Can provide a biased pooled estimate when there is baseline imbalance across randomised trials. Generally only a problem when there are a small number of trials with few participants May provide less precision compared with meta-analysing ANCOVA results May require assumptions to be made about missing data Will require data manipulation (generally less than option 2)

Option	Advantages	Disadvantages
 3) Meta-analysis using results from only one analysis method (SAFV or SACS): Meta-analyse estimates using the same analysis method. This approach may involve imputing missing statistics (e.g. correlations) 	 Removes bias from trialists selectively reporting analyses 	 Can provide a biased pooled estimate when there is baseline imbalance across randomised trials. Generally only a problem when there are a small number of trials with few participants May provide less precision compared with meta-analysing ANCOVA results May require assumptions to be made about missing data Will require data manipulation (generally less than option 2)
4) Meta-analysis using a mix of results from different analysis methods: The meta-analysis may include estimates from SAFV, SACS, and ANCOVA	 Generally less imputation and data manipulation required 	 Prone to selective reporting of results May provide less precision compared with meta-analysing ANCOVA results



Calcium supplementation on body weight (Trowman 2006 Br J Nut)

Trial	Year		Baseline	(weight	kg)	Follow-up (we	eight kg)	Change (we	eight kg)
		Int	ervention		Control	Intervention	Control	Intervention	Control
		n	Mean (SD)	n	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)
Chee	2003	91	56.1 (8.9)	82	57.2 (9.4)	56.1 (?)	57.4 (?)	0.0 (2.6) ^a	0.2 (2.6) ^a
Jensen	2001	25	94.6 (14.0) ^a	27	93.8 (14.0) ^a	89.0 (12.7) ^a	89.1 (14.7) ^a	-5.6 (?)	-4.7 (?)
Lau	2001	95	56.9 (7.1)	90	58.9 (7.5)	57.4 (?)	58.6 (?)	0.5 (2.6)ª	-0.3 (2.7) ^a
Reid	2002	111	66.0 (10.0)	112	68.0 (11.0)	65.7 (?)	67.9 (?)	-0.3 (1.8)	-0.1 (2.4)
Shapses 1 ^c	2004	17	84.1 (9.4)	19	89.4 (10.3)	77.1 (?)	82.1 (?)	-7.0 (4.6)	-7.3 (5.3)
Shapses 2 ^c	2004	11	85.9 (9.2)	11	94.2 (15.7)	79.2 (?)	86.6 (?)	-6.7 (2.6)	-7.6 (5.7)
Shapses 3 ^c	2004	18	93.7 (13.6)	24	93.5 (14.3)	87.0 (?)	89.2 (?)	-6.7 (5.5)	-4.3 (3.5)
Winters-Stone	2004	13	57.2 (4.9)	10	54.1 (7.2)	56.3 (4.3)	54.8 (7.2)	-0.9 (?)	0.7 (?)
Zemel	2004	11	99.8 (14.9)	10	103.1 (19.3)	91.2 (?)	96.5 (?)	-8.6 (5.3)ª	-6.6 (8.2) ^a

a Calculated from the standard error

b Follow-up sample size ntrt = 24 and nctrl = 24

c Shapses et al (Shapses et al, 2004) report on three randomised controlled trials.

Trials 1, 2, and 3 include postmenopausal women, postmenopausal women special diet, and premenopausal women respectively.

Option 3 (v1): Meta-analysis of results from only one analysis method

- Trowman (2006) used this option
- For each trial, estimated treatment effect by calculating the difference in mean follow-up measurements
- For missing SDs at follow-up, they assumed the baseline SD



Calcium supplementation on body weight (Trowman 2006 Br J Nut)

Trial	Year		Baseline	(weight	kg)	Follow-up (we	eight kg)	Change (we	eight kg)
		Int	ervention		Control	Intervention	Control	Intervention	Control
		n	Mean (SD)	n	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)
Chee	2003	91	56.1 (8.9)	82	57.2 (9.4)	56.1 (8.9)	57.4 (9.4)	0.0 (2.6) ^a	0.2 (2.6) ^a
Jensen	2001	25	94.6 (14.0) ^a	27	93.8 (14.0) ^a	89.0 (12.7) ^a	89.1 (14.7) ^a	-5.6 (?)	-4.7 (?)
Lau	2001	95	56.9 (7.1)	90	58.9 (7.5)	57.4 (7.1)	58.6 (7.5)	0.5 (2.6)ª	-0.3 (2.7) ^a
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Shapses 1°	2004	17	84.1 (9.4)	19	89.4 (10.3)	77.1 (9.4)	82.1 (10.3)	-7.0 (4.6)	-7.3 (5.3)
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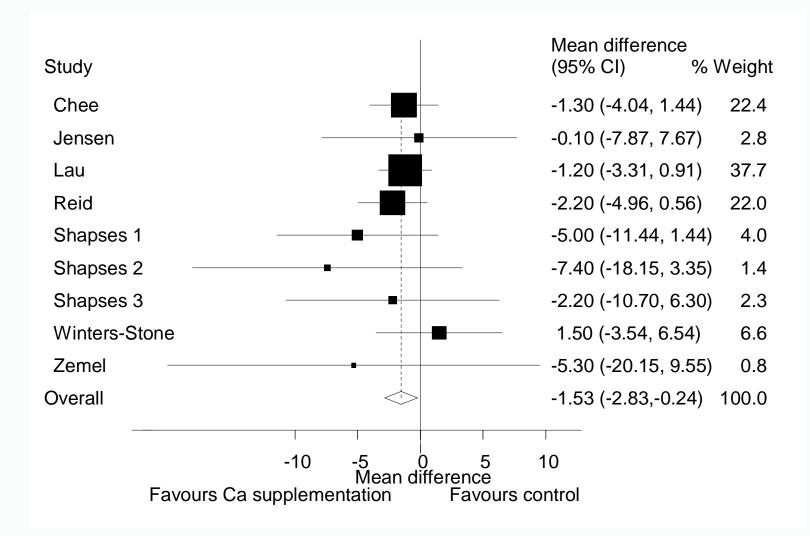
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Trials 1, 2, and 3 include postmenopausal women, postmenopausal women special diet, and premenopausal women respectively.

Combining intervention estimates from SAFV only



Option 3 (v2): Meta-analysis of results from only one analysis method

- Use change scores
 - Impute missing change score SDs, in each intervention group, by calculating the median of the other SDs
- Many other options for imputing missing SDs

e.g. in trials with baseline SDs and change SDs, assume follow-up SDs are the same as baseline SDs (seems reasonable assumption based on Jensen 2001 and Winters-Stone 2004) then calculate correlations and SDs at follow-up using

$$Corr_{int} = \frac{SD_{int,X}^2 + SD_{int,Y}^2 - SD_{int,C}^2}{2 \times SD_{int,X} \times SD_{int,Y}}$$

$$SD_{int,C} = \sqrt{SD_{int,X}^2 + SD_{int,Y}^2 - (2corr_{int} \times SD_{int,X} \times SD_{int,Y})}$$

Wiebe 2006 J Clin Epi; Balk 2012 AHRQ



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Calcium supplementation on body weight (Trowman 2006 Br J Nut)

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		N	Mean (SD)	n	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)
Chee	2003	91	56.1 (8.9)	82	57.2 (9.4)	56.1	57.4	0.0 (2.6) ^a	0.2 (2.6) ^a
Jensen	2001	25	94.6 (14.0) ^a	27	93.8 (14.0) ^a	89.0 (12.7) ^a	89.1 (14.7) ^a	-5.6 (2.6)	-4.7 (3.5)
Lau	2001	95	56.9 (7.1)	90	58.9 (7.5)	57.4	58.6	0.5 (2.6)ª	-0.3 (2.7)ª
Reid	2002	111	66.0 (10.0)	112	68.0 (11.0)	65.7	67.9	-0.3 (1.8)	-0.1 (2.4)
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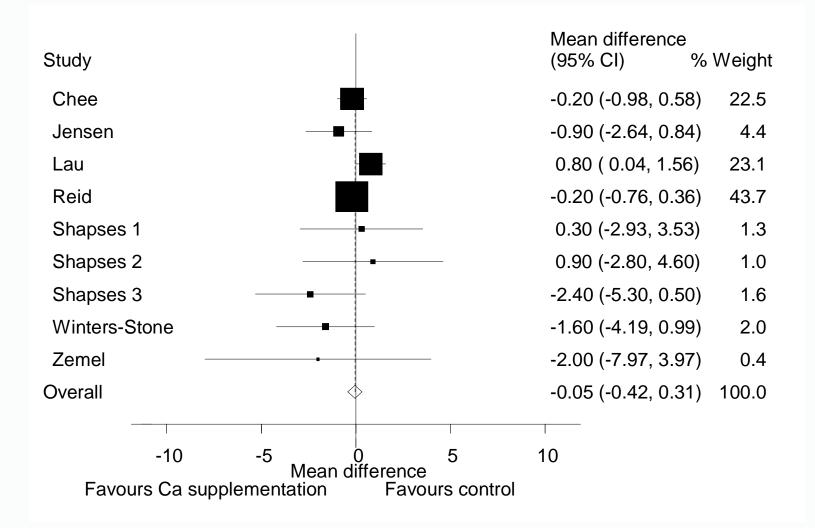
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Trials 1, 2, and 3 include postmenopausal women, postmenopausal women special diet, and premenopausal women respectively.

Combining intervention estimates from SACS only



Option 4: Meta-analysis using a mix of results from different analysis methods



Calcium supplementation on body weight (Trowman 2006 Br J Nut)

Trial	Year	Baseline (weight kg)			Follow-up (weight kg)		Change (weight kg)		
		Int	tervention	Control		Intervention	Control	Intervention	Control
		N	Mean (SD)	n	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)
Chee	2003	91	56.1 (8.9)	82	57.2 (9.4)			0.0 (2.6) ^a	0.2 (2.6) ^a
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Lau	2001	95	56.9 (7.1)	90	58.9 (7.5)			0.5 (2.6)ª	-0.3 (2.7) ^a
Reid	2002	111	66.0 (10.0)	112	68.0 (11.0)			-0.3 (1.8)	-0.1 (2.4)
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Shapses 3 ^c	2004	18	93.7 (13.6)	24	93.5 (14.3)			-6.7 (5.5)	-4.3 (3.5)
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Zemel	2004	11	99.8 (14.9)	10	103.1 (19.3)			-8.6 (5.3)ª	-6.6 (8.2) ^a

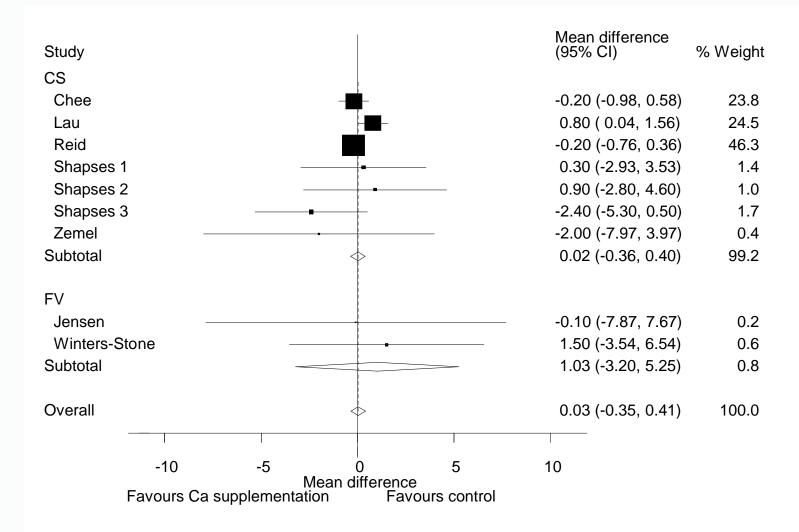
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Combining intervention estimates from SAFV and SACS



Which option?

		Meta-analysis options				
Domain		2) Only ANCOVA	3) Only one (SAFV or SACS)	4) Mix (SAFV, SACS, and ANCOVA)		
Bias (few small trials)	Chance baseline imbalance across trials	\checkmark				
	Selective reporting	\checkmark	\checkmark			
Precision	No heterogeneity	\checkmark				
	Heterogeneity	=	=	=		
Practical issues		×	×	\checkmark		

McKenzie 2015 Res Synth Methods



Which option?

 In many circumstances combining estimates calculated from a mix of analysis methods is reasonable (option 4)

Include available ANCOVA estimates where possible

- If combining estimates based on only one analytical method (SAFV or SACS), options for choice of method include
 - the analysis method most frequently reported
 - the analysis method that is likely to yield the greatest precision (correlations likely to be large → use SACS; correlations likely to be small → use SAFV)



References

- Balk EM, Earley A, Patel K, Trikalinos TA, Dahabreh IJ: Empirical Assessment of Within-Arm Correlation Imputation in Trials of Continuous Outcomes. Methods Research Report. (Prepared by the Tufts Evidence-based Practice Center under Contract No. 290-2007-10055-I.). In: AHRQ Publication. Rockville, MD: Agency for Healthcare Research and Quality; 2012.
- McKenzie JE, Herbison GP, Deeks JJ. Impact of analysing continuous outcomes using final values, change scores and analysis of covariance on the performance of meta-analytic methods: a simulation study. Res Synth Methods. 2015.
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- Wiebe N, Vandermeer B, Platt RW, Klassen TP, Moher D, Barrowman NJ: A systematic review identifies a lack of standardization in methods for handling missing variance data. J Clin Epi. 2006, 59(4):342-353.



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- Standard meta-analytic methods assume normality in the distribution of the means (not raw data)
- Many outcomes are not normally distributed. Examples include:
 - Concentrations
 - e.g. urinary iodine
 - Ratio or reciprocal measures
 - e.g. ratio of partial pressure of arterial oxygen to fraction of inspired oxygen
 - Resource use
 - e.g. length of stay
 - Assessment scales
 - e.g. large proportion of 'normal' participants fall towards one extreme of the scale

Higgins 2008 Stats in Med



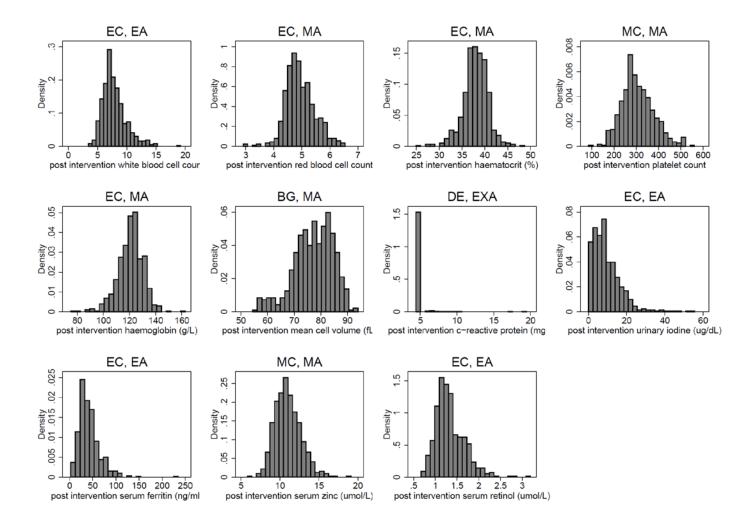
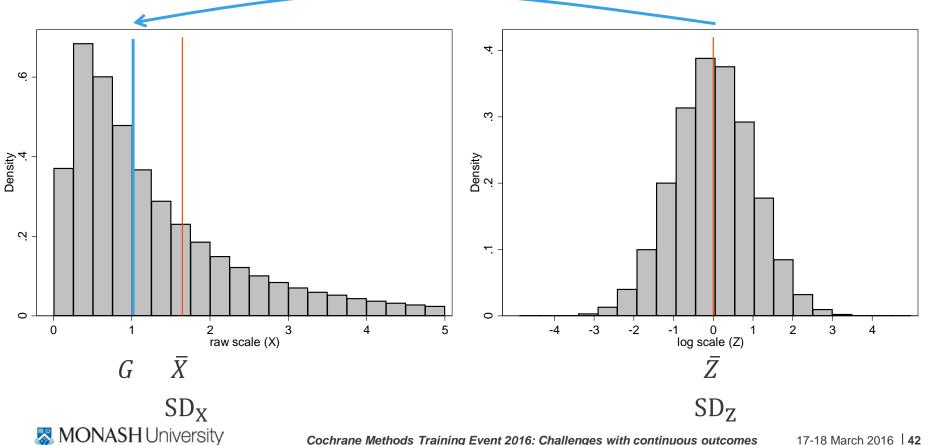


Figure 3: Histograms of post biochemical variables from Thailand RCT First abbreviation = classification based on tail weight (U = Uniform, BG = Below Gaussian, G = Gaussian, MC = Moderate Contamination, EC = Extreme Contamination, DE = Double Exponential), second abbreviation = classification based on asymmetry (S = Near Symmetry, MA = Moderate Asymmetry, EA = Extreme Asymmetry, EXA = Exponential Asymmetry).

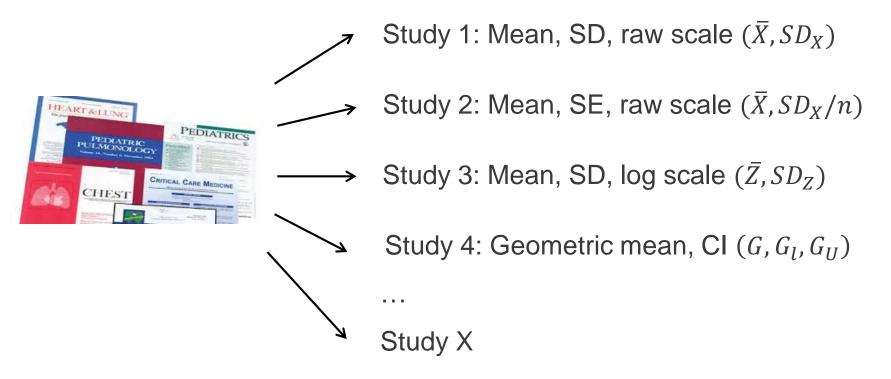
Dealing with skewed data in studies

Common approach to dealing with skewed data is to log transform the observations, then undertake the analysis on the log scale



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- Meta-analytic methods are likely to be valid in large trials even when the outcome is skewed, but practical issues arise
- Same outcome: different scales (raw, log), different statistics



- Aim to include as many trials in the one meta-analysis as possible
- To achieve this, we need to transform the summary statistics from one scale to another

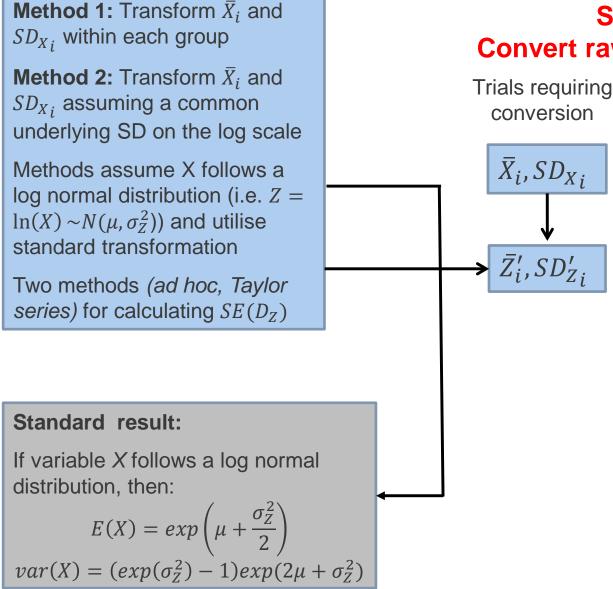
STATISTICS IN MEDICINE Statist. Med. 2008; **27**:6072–6092 Published online 17 September 2008 in Wiley InterScience (www.interscience.wiley.com) DOI: 10.1002/sim.3427

Meta-analysis of skewed data: Combining results reported on log-transformed or raw scales

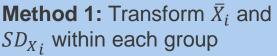
Julian P. T. Higgins^{*,†}, Ian R. White and Judith Anzures-Cabrera

MRC Biostatistics Unit, Institute of Public Health, Robinson Way, Cambridge CB2 0SR, U.K.





Scenario 1: Convert raw scale to log scale



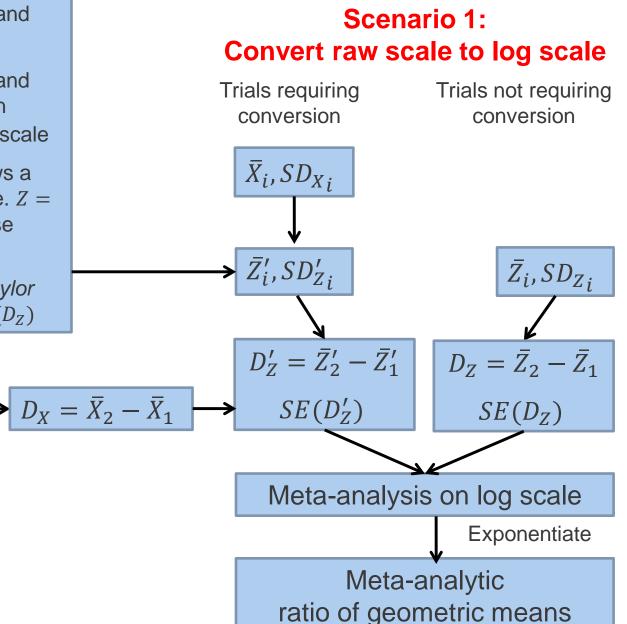
Method 2: Transform \overline{X}_i and SD_{X_i} assuming a common underlying SD on the log scale

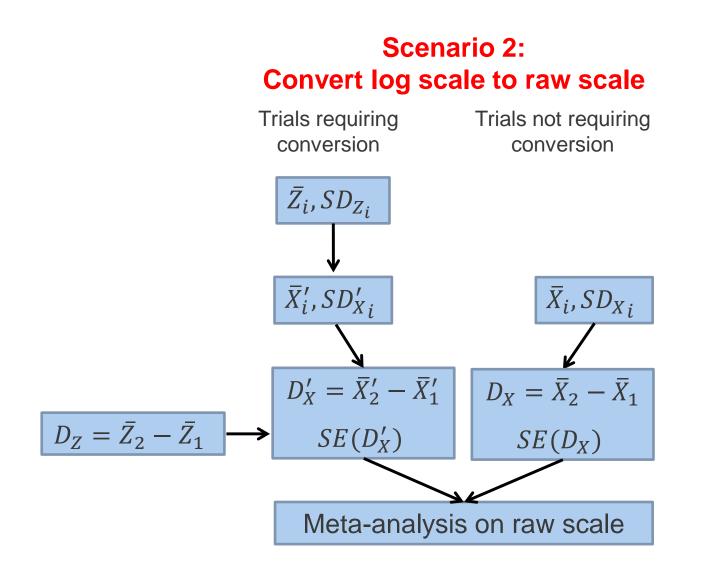
Methods assume X follows a log normal distribution (i.e. $Z = \ln(X) \sim N(\mu, \sigma_Z^2)$) and utilise standard transformation

Two methods (ad hoc, Taylor series) for calculating $SE(D_Z)$

Method 3: Targets difference between the groups (D_X) , rather than group means.

Method does *not* assume X follows a log normal distribution





Meta-analysis from a systematic review (Sagoo et al)

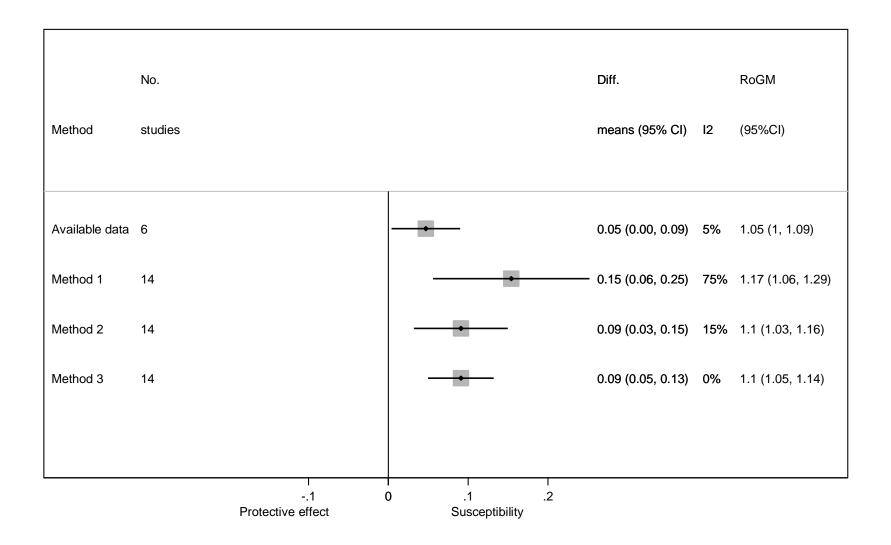
Examines association between triglyceride level and being a carrier or noncarrier of the D9N polymorphism in the LPL gene.

	Carriers					Non-carriers						
		Raw		Log			Ra	W	Log			
	n	Mean	SD	Mean	SD	n	Mean	SD	Mean	SD		
Boer 2003b	34			0.31	0.58	1002			0.33	0.53		
Copenhagen	241	2.10	1.46	1.05	0.37	8429	1.85	1.54	0.98	0.34		
CDRFMP	14	2.05	1.21			364	1.57	1.11				
EARS I & II	71	1.12	0.34			1608	0.99	0.80				
ECTIM	22	1.82	1.46			784	1.84	1.47				
Ehrenborg 1997	15	1.01	0.36		_	77	0.99	0.53				
Ferencak 2003	5	2.04	0.92		_	195	1.81	0.84				
FOS	58	1.61	0.72	_	_	2200	1.38	1.16				
Glisic 2003b	4	2.42	1.53	0.74	0.60	129	1.64	0.94	0.37	0.49		
Reykjavik	10	1.64	1.64	0.20	0.74	274	1.04	0.49	-0.05	0.42		
Rios 2003	10	1.60	0.70	0.39	0.41	187	1.75	0.92	0.43	0.50		
Schulte 1996	17	1.96	0.82		_	644	1.56	0.82				
Talmud 1998	12	1.35	0.52			96	1.27	0.52				
Yang 2004	235	2.39	1.46	0.74	0.50	1275	2.34	1.26	0.73	0.49		

Table I. Data available for D9N polymorphism in the lipoprotein lipase gene and triglyceride levels.

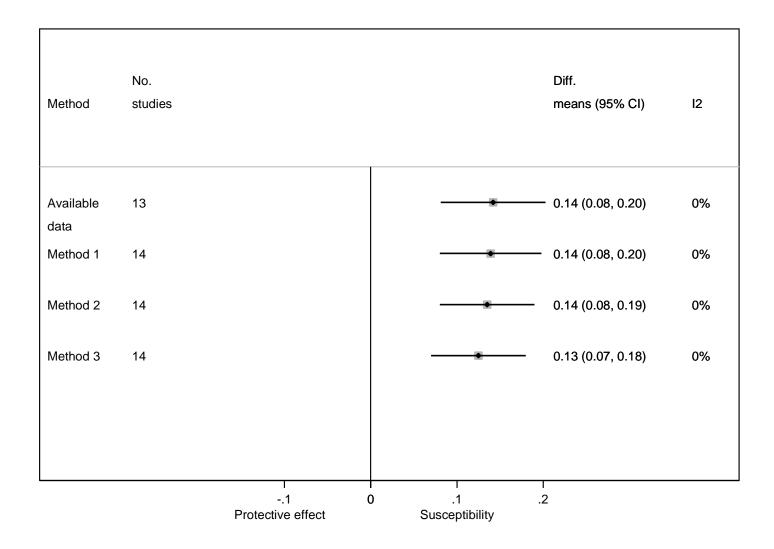
Raw to log scale

Difference in mean log triglyceride level (Carriers - Non-carriers) using alternative conversions



Log to raw scale

Difference in mean raw triglyceride level (Carriers – Non-carriers) using alternative conversions



Which conversion method? Which direction?

Which conversion method?

- Not a uniformly preferable method
- All methods reasonably robust to data having distributions other than log normal
- Method 1 preferable when SDs differ across groups; when SDs are similar, greater precision obtained using Method 2

Which direction? Raw to log scale OR log to raw scale?

- Use the scale most frequently used
- Scale best meeting meta-analytic assumptions (scale believed to be less skewed)
- Meta-analysis on the log-scale may reduce heterogeneity

MONASH University

Length of intubation (hours)

Study	High dose opioid						Significance as reported by authors				
	n	Mean	SD	Median	Range	n	Mean	SD	Median	Range	
Slogoff 1989 Enflurane Halothane Isoflurance	254	22.8	12.3			257 253 248	14.5 16.8 14.7	6.3 7.2 5.4			ANOVA p = 0.001
Bell 1994	19			12.96		20			4.42		p = 0.0005
Cheng 1996	51	18.9	1.4			51	4.1	1.1			p < 0.02
Myles 1997	66	21.5	5.1	12.3	3.5-31.5	58	11.4	9.9	·		p = 0.006
Silbert 1998	42			7.0	2.1-19	38			4.0	0.5-15.5	p < 0.01
Michalopoulos 1998	72	11.6	1.3			72	7.3	0.7			p = 0.0001
Sakaida 1998	20	14.5	4.5	15	6-25.3	20	5.6	1.6	5.2	3.5-9	p < 0.05
Berry 1998	42			12.62	8.32-20.67	43			1.83	0.1-4.25	significant
Myles 2001	24			9.7	1.1-25	24			6.5	0.4-150	?significant

Anesthesiology 2003; 99:982-7

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A Systematic Review of the Safety and Effectiveness of Fast-track Cardiac Anesthesia

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Source: Doug Altman

Dealing with non-parametric statistics

- Assume that the data are (close to) lognormal
 - median ~ geometric mean
 - Convert centiles to mean and SD on the log scale
 - Converting ranges see: Walter 2007 J Clin Epi; Hozo 2005 BMC Med Res Methodol
 - Converting IQR: Section 7.7.3.5 Cochrane Handbook; Wan 2014 BMC Med Res Methodol
- Combine using conversion approaches in Higgins 2008 Stats Med



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