IPS / Translational Bioinformatics

Modeling Baseline in Repeated Measures Studies

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Adjusting for Baseline in Model (ANCOVA)

Pros	Cons

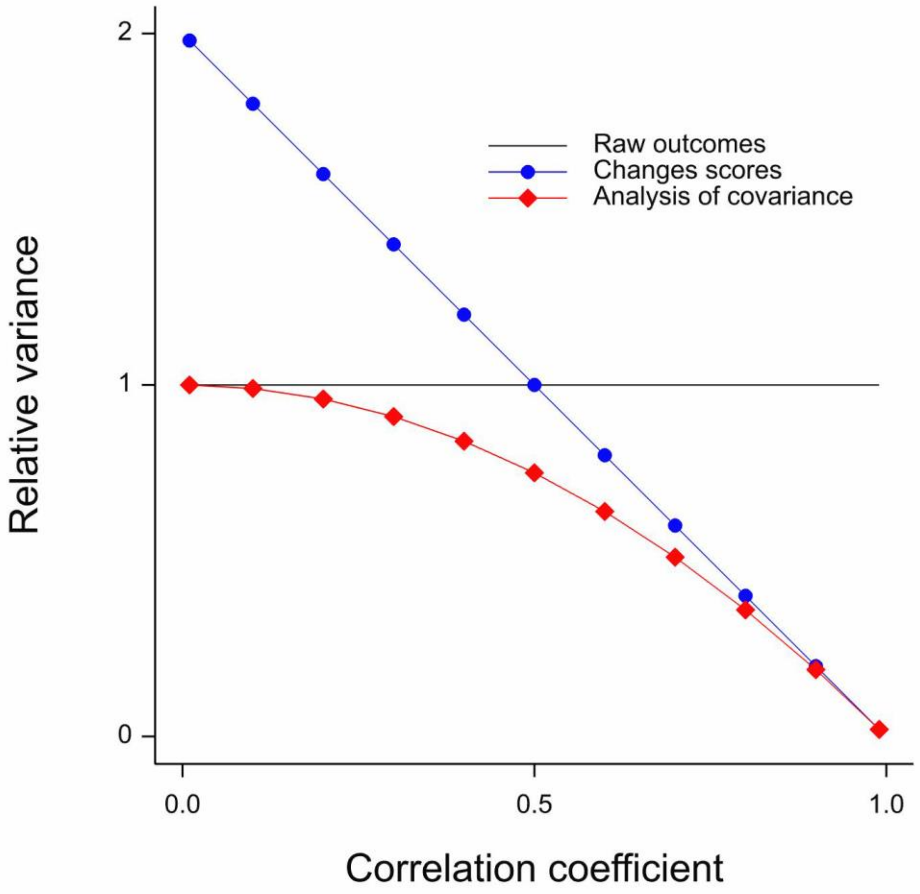
• Unbiased estimator for treatment effect in many scenarios even when there are differences at baseline
  • See Senn paper
  • If factors are balanced, reduces variance of estimated treatment effect
    • Increases power
	• Can’t make contrast estimating change from baseline.
	  • Is this a contrast we should be making? See https://discourse.datamethods.org/t/rms-discussions/3275/117 (posts 113-118); BBR notes 14.4
	  • “Regression to the mean” will artificially affect “within patient” change scores

• Adjusts for unknown confounders	• Need MI if patient is missing baseline measure, otherwise lose all follow-up visits • Can impute mean baseline (see Kenward paper)
• Allows for nonlinear baseline effect	
• Baseline tends to be strongest predictor	

Baseline as Outcome (Change Score)

Pros	Cons
• Can estimate contrast for change from baseline	• Assumes no relationship between pre and change from baseline
• Not necessary to impute missing baseline values	• Assumes outcome is not part of inclusion/exclusion criteria
	• More scenarios where imbalance at baseline will yield biased treatment effect
	• Reliant on appropriate transformation of outcome, otherwise subtraction will be on wrong scale
	• Does not work with ordinal scales
	• Assumes baseline has effect on outcome (e.g. if baseline were noisy, calculating change score will yield biased result whereas including baseline as covariate will yield coefficient of 0). • If correlation is <0.5, then change score is doing more harm than good (worse than ignoring baseline completely). See figure in Senn Chapter 7.

Summary of comparison between Change Score and ANCOVA



Miscellaneous

- Including baseline in model will allow “change score” as outcome, but only in linear models, not binary outcomes, etc. Rather should always model raw values.