



Regionalt kunnskapssenter
for barn og unge
– Psykisk helse og barnevern

Analyse av endring i longitudinelle studier: Justering for utgangsverdi?

Presentasjon på RBUP, Oslo, 3 november 2014
og RKBU, Trondheim, 14 november 2014

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http://folk.ntnu.no/slyderse/Adjust_for_baseline/Pres3Nov2014

Forhåndsomtale:

I studier med to eller flere målingstidspunkt vil en ofte studere hva som predikerer endring: I en randomisert kontrollert studie, hvilken behandlingsgruppe får mest gunstig endring i utfallsmålet fra før til etter behandling? I en observasjonell studie, hvilke(n) eksponering(er) påvirker endring og i hvor stor grad?

Regresjonsanalyse med etter-verdi som avhengig variabel og før-verdi samt gruppe som kovariater (ANCOVA) er en egnet metode for en RCT. I en observasjonell studie derimot, vil ANCOVA vanligvis gi helt feil resultater, noe mange forskere ikke er klar over.

Mixed models er egnet både i RCT og observasjonelle studier. Dette er i prinsippet det samme som vekstmodeller i SEM (Structural equation modellering).

Eksempler:

- Randomisert kontrollert studie (RCT): (Vickers and Altman 2001)
- Observasjonell studie: (Breidablik et al. 2009)

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Hva mener vi med endring?

Alternative definisjoner av og analysemodeller
(Fitzmaurice et al. 2011; Twisk 2013)

Alternativ 1- 5:

Relevant ved analyse av bare en etter-verdi (av gangen).

Alternativ 6 og 7:

Mest relevant ved mer enn to tidspunkt.

1.

Absolutt endring: Relevant ved observasjonelle studier

$$\Delta Y_i = Y_{i2} - Y_{i1}$$

2.

Relativ endring:

$$\Delta Y_i = \frac{Y_{i2} - Y_{i1}}{Y_{i1}} \times 100\%$$

3.

Endring relativ til gulv/tak effekt:

$$\text{Når } Y_{i2} > Y_{i1} : \Delta Y_i = \frac{(Y_{i2} - Y_{i1})}{(Y_{\max} - Y_{i1})} \times 100\%$$

$$\text{Når } Y_{i2} < Y_{i1} : \Delta Y_i = \frac{(Y_{i2} - Y_{i1})}{(Y_{i1} - Y_{\min})} \times 100\%$$

$$\text{Når } Y_{i2} = Y_{i1} : \Delta Y_i = 0$$

Merk at

$$\Delta Y_i = \frac{(Y_{i2} - Y_{i1})}{(Y_{\max} - Y_{\min})} \times 100\%$$

bare er en reskalering av absolutt endring.

4.
ANCOVA: Relevant (nesten bare) ved RCT

$$Y_{i2} = \beta_0 + \beta_1 Y_{i1} + \beta_2 Intervention + \dots + \varepsilon_i$$

Enkelte forfattere foreslår regresjonsanalyse med absolutt endring som avhengig variabel og før-verdi som kovariat:

$$Y_{i2} - Y_{i1} = \beta_0 + \beta_1^* Y_{i1} + \beta_2 Intervention + \dots + \varepsilon_i$$

Men dette er ekvivalent med ANCOVA:

$$Y_{i2} = \beta_0 + (\beta_1^* + 1)Y_{i1} + \beta_2 Intervention + \dots + \varepsilon_i$$

Eksempel: Data fra Vickers & Altman (2001)

Coefficients ^a							
Model	Unstandardized Coefficients			Standardized Coefficients		95.0% Confidence Interval	
	B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound
1							
Constant	23.987	9.106		2.634	.011	6.392	41.582
pre-treatment score	-.173	.164	-.093	-.105	.918	-.500	.155
intervention	12.035	4.288	.530	2.806	.009	4.393	19.677

a. Dependent Variable: post-treatment score

Coefficients ^a							
Model	Unstandardized Coefficients			Standardized Coefficients		95.0% Confidence Interval	
	B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound
1							
Constant	25.957	5.169		5.024	<.001	15.692	36.222
pre-treatment score	-.253	.63	-.243	-.403	.697	-1.512	1.002
intervention	12.763	1.263	.980	10.065	<.001	10.238	15.288

a. Dependent Variable: change score

5.
Bare bruke etter-verdi:
 Y_{i2}

Eksempel på analyse av RCT i Vickers & Altman (2001):

Follow-up (alternativ 5)
Change score (alternativ 1)
ANCOVA (alternativ 4)

6.
(Alternative 1 in (Fitzmaurice, Laird, & Ware 2011), page 128, Section 5.7)

Retain baseline as part of the outcome vector and make no assumptions about group differences at baseline

$$Y_{i1} = \beta_0 + \beta_1 x_i + \varepsilon_{i1}$$

$$Y_{i2} = \beta_0 + (\beta_1 + \beta_2)x_i + \beta_3 + \varepsilon_{i2}$$

Der man evt legger restriksjoner på kovarians-strukturen på $(\varepsilon_{i1}, \varepsilon_{i2})'$.

Hvis $x_i = 0(1)$ når individ nr i er i gruppe 0(1): Nullhypotese:

Ingen gruppe-effekt, dvs endring er lik i de to gruppene: $\beta_3 = 0$

Dette gir ca samme svar som å bruke absolutt endring som avhengig variabel (Alternativ 1). (Samtale med Fitzmaurice, 23 aug. 2009)

Tilsvare mixed model.

7.
(Alternative 2 in (Fitzmaurice, Laird, & Ware 2011), page 128, Section 5.7)
Retain baseline as part of the outcome vector and assume the group means are equal at baseline, as might be appropriate in a randomized controlled trial.
Som ovenfor, uten β_1 i modellen.

Coefficients ^a							
Model	Unstandardized Coefficients			Standardized Coefficients		95.0% Confidence Interval	
	B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound
1							
Constant	87.785	7.574		11.590	<.001	72.517	103.053
baseline score	17.206	4.372	.445	3.935	.001	8.444	26.008

a. Dependent Variable: post-treatment score

Coefficients ^a							
Model	Unstandardized Coefficients			Standardized Coefficients		95.0% Confidence Interval	
	B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound
1							
Constant	87.785	7.574		11.590	<.001	72.517	103.053
baseline score	17.206	4.372	.445	3.935	.001	8.444	26.008

a. Dependent Variable: change score

Coefficients ^a							
Model	Unstandardized Coefficients			Standardized Coefficients		95.0% Confidence Interval	
	B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound
1							
Constant	25.957	5.169		5.024	<.001	15.692	36.222
baseline score	12.726	1.263	.980	10.065	<.001	10.238	15.288
post-treatment score	-.270	.185	-.145	-.145	.853	-.633	.093

a. Dependent Variable: post-treatment score

Mixed model: Need datafile in long format (one case per time point per subject)

Estimates of Fixed Effects ^a						
Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval
Intercept	52.62420	2.886384	190.90	18.231	.000	46.85203 58.39637
Time	0.170370	2.647901	50.000	2.029	.007	-2.445177 3.785917
Age at baseline	6.474374	4.212241	190.90	1.531	.137	-1.911365 14.860113
Time * Age at baseline	10.676330	4.761836	80.000	2.242	.034	1.188565 20.16410

a. Dependent Variable: Score

As expected, the result is similar to using absolute change as dependent variable.

When is baseline adjustment useful in analyses of change?

Should we use absolute change (without adjusting for baseline) or ANCOVA?

“The answer depends critically on whether the data arise from an observational study or a randomized trial. If the study is an observational one, ... it is usually not advisable to employ the analysis of covariance ...” (Fitzmaurice, Laird, & Ware 2011) page 124 - 128.

In a randomized trial, it is a good recommendation to adjust for baseline values by using after treatment score as dependent variable, and before treatment score and group indicator as covariates (Vickers & Altman 2001). (ANCOVA)

“In general, the analysis of longitudinal data from a randomized trial is the only setting in which we recommend adjustment for baseline through analysis of covariance. In that setting, in contrast to observational studies, adjustment leads to meaningful tests of hypotheses of scientific interest. Moreover the tests based on the analysis of covariance approach will be more powerful...”

“When the covariance among repeated measures is assumed to have a compound symmetry pattern, with common variance σ^2 and common correlation ρ , the relative efficiency (ratio of the variance of the two estimators) is given by

$$\frac{1}{n} \{1 + (n-1)\rho\}.”$$

(Fitzmaurice, Laird, & Ware 2011) page 126.

For example, with $n = 2$ (one follow-up measure) and $\rho = 0.4$ (realistic for within-person measurements), the relative efficiency is $\frac{1}{2} \{1 + (2-1)0.4\} = 0.7$.

“Adjustment for baseline in the analysis of longitudinal change is a topic that has generated heated debate among analysts. When longitudinal data arise from an observational study, the two methods of adjusting for baseline described in this section can yield discernibly different and, apparently different results. This conundrum is also known as *Lord's paradox* (named after Frederic Lord, who eloquently brought this issue into light) and **has led many researchers astray over the years**. The paradox lies in the interpretation of the two types of analyses and is resolved by noting that these two alternative methods for adjusting for baseline answer qualitatively different scientific questions when the data arise from an observational study. This can be illustrated in the simplest setting where there are two groups or sub-populations (e.g. males and females) measured at two occasions. ...” (Fitzmaurice, Laird, & Ware 2011) page 126.
See Figure 1 (Lord 1967)

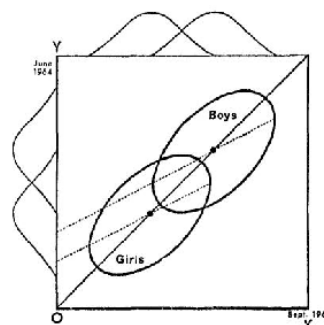
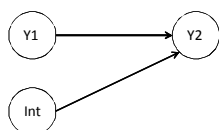


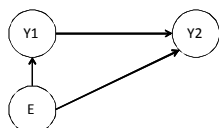
FIG. 1. Hypothetical scatterplots showing initial and final weight for boys and for girls.
Lord (1967)

Den store forskjellen:

RCT:
Utgangsverdi (Y1) er
uavhengig av
behandling
(Intervensjon)



Observasjonell studie:
Eksponering (E) som
påvirker
utgangsverdien (Y1)



Breidablik, H.J., Meland, E., & Lydersen, S. 2009. Self-rated health during adolescence: stability and predictors of change (Young-HUNT study, Norway). Eur.J.Public Health, 19, (1) 73-78

Feilaktig bruk av justering for utgangsverdi (ved T1) gjorde at deler av Tabell 4 ble feil. Dette ble senere kommentert i sammenskrivningen til avhandlingen til Breidablikk.

"In conclusion, it is the study design and the scientific question of interest ... that should primarily determine the choice of analytic methods for adjusting for the baseline response." (Fitzmaurice, Laird, & Ware 2011) page 127.

An in-depth coverage of analysis of observational data is given in (Glymour et al. 2005).

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