

Design of dose-escalation trials

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Abstract

In one form of dose-escalation trial, several cohorts of subjects are recruited. Each cohort takes part at a different time period. The doses are ordinally labelled $0, 1, \dots$. Because higher doses may have more adverse side-effects, no subject can be exposed to dose i until some information is obtained about the effect of dose $i - 1$.

One possibility is to use dose i for everyone in cohort i . Then there is no blinding; moreover, dose effects are completely confounded with cohort effects and period effects.

A modification of this uses a certain number of placebo subjects in each cohort. If there are no cohort effects then the proportion of placebo in each cohort should be such that the design is equireplicate if it proceeds to the planned largest dose. If there are cohort effects, then more precise comparisons between doses can be made if half of each cohort receives placebo.

I shall discuss a new design that does at least as well as both of these, whether or not there is a cohort effect.

Design of the TeGenero trial

Cohort	TGN1412		Placebo
	Dose mg/kg bodyweight	Number of Subjects	Number of Subjects
1	0.1	6	2
2	0.5	6	2
3	2.0	6	2
4	5.0	6	2

What happened to Cohort 1 on 13 March 2006

Healthy Volunteer	Randomised to	Time of intravenous administration	Time of transfer to critical care
A	TGN1412 8.4mg	0800	2400
B	Placebo	0810	
C	TGN1412 6.8mg	0820	2350
D	TGN1412 8.8mg	0830	0030
E	TGN1412 8.2mg	0840	2040
F	TGN1412 7.2mg	0850	0050
G	TGN1412 8.2mg	0900	0100
H	Placebo	0910	

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- ▶ proper interval between dosing subjects
(sudden adverse effects → do not dose further subjects;
delayed adverse effects → ill subjects can be treated one by one)

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- ▶ protocol

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- ▶ sequential choice of dose

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- ▶ sequential choice of dose
- ▶ allocation of ordinal doses to cohorts.

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- ▶ preclinical / clinical interface
- ▶ protocol
- ▶ sequential choice of dose
- ▶ **allocation of ordinal doses to cohorts.**

Planned analysis of the TeGenero trial

Cohort	TGN1412		Placebo
	Dose	Number	Number
1	1	6	2
2	2	6	2
3	3	6	2
4	4	6	2

If all responses are uncorrelated with variance σ^2 then
Variance (dose i – placebo) in cohort i is $(\frac{1}{6} + \frac{1}{2}) \sigma^2 = \frac{2}{3} \sigma^2$

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From the protocol: “data of subjects having received placebo will be pooled in one group for analyses”

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From the protocol: “data of subjects having received placebo will be pooled in one group for analyses”

Variance (dose i – placebo) is $(\frac{1}{6} + \frac{1}{8}) \sigma^2 = \frac{7}{24} \sigma^2$

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Variance (dose i – placebo) in cohort i is $(\frac{1}{6} + \frac{1}{2}) \sigma^2 = \frac{2}{3} \sigma^2$

From the protocol: “data of subjects having received placebo will be pooled in one group for analyses”

Variance (dose i – placebo) is $(\frac{1}{6} + \frac{1}{8}) \sigma^2 = \frac{7}{24} \sigma^2$ **if there are no cohort effects**

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Variance (dose i – dose j) is $(\frac{1}{6} + \frac{1}{6}) \sigma^2 = \frac{1}{3} \sigma^2$ if there are no cohort effects

Are there cohort effects?

- ▶ Different types of people can volunteer at different times.

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There have been many trials, in many topics, where, with hindsight, cohort effects swamp treatment effects.

Analysis of the TeGenero trial with cohort effects

Cohort	TGN1412		Placebo
	Dose	Number	Number
1	1	6	2
2	2	6	2
3	3	6	2
4	4	6	2

$$\text{Variance (dose } i - \text{ placebo) in cohort } i = \left(\frac{1}{6} + \frac{1}{2} \right) \sigma^2 = \frac{2}{3} \sigma^2.$$

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$$\text{Variance (dose } i - \text{ placebo) in cohort } i = \left(\frac{1}{6} + \frac{1}{2} \right) \sigma^2 = \frac{2}{3} \sigma^2.$$

Estimator of (dose i – dose j) =

$$\begin{aligned} & [\text{estimator of (dose } i - \text{ placebo) in cohort } i] - \\ & [\text{estimator of (dose } j - \text{ placebo) in cohort } j] \end{aligned}$$

Analysis of the TeGenero trial with cohort effects

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$$\text{So variance (dose } i - \text{ dose } j) = \left(\frac{2}{3} + \frac{2}{3} \right) \sigma^2 = \frac{4}{3} \sigma^2.$$

Senn's proposed design

Cohort	TGN1412		Placebo
	Dose	Number	Number
1	1	4	4
2	2	4	4
3	3	4	4
4	4	4	4

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Cohort	TGN1412		Placebo
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$$\text{Variance (dose } i - \text{ placebo) in cohort } i = \left(\frac{1}{4} + \frac{1}{4} \right) \sigma^2 = \frac{1}{2} \sigma^2 < \frac{2}{3} \sigma^2.$$

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	Dose	Number	Number
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Variance (dose i – placebo) in cohort $i = \left(\frac{1}{4} + \frac{1}{4}\right) \sigma^2 = \frac{1}{2} \sigma^2 < \frac{2}{3} \sigma^2$.

So variance (dose i – dose j) = $\left(\frac{1}{2} + \frac{1}{2}\right) \sigma^2 = \sigma^2$

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The TeGenero design is **inadmissible** because everything can be estimated, from the same resources, with smaller variance, by another design.

Dose-escalation trials: standard designs

There are n doses, with dose $1 < \text{dose } 2 < \dots < \text{dose } n$.

0 denotes the placebo.

There are n cohorts of m subjects each.

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There are n cohorts of m subjects each.

Cohort 1 subjects may receive only dose 1 or placebo.

In Cohort i , some subjects receive dose i ;
no subject receives dose j if $j > i$.

Put s_{ik} = number of subjects who get dose i in period k . Then

$$s_{ik} > 0 \quad \text{if} \quad i = k$$

$$s_{ik} = 0 \quad \text{if} \quad i > k$$

Scaled variance

Assume that the expectation of the response of a subject who gets dose i in cohort k is $\tau_i + \beta_k$, and that responses are uncorrelated with common variance σ^2 .

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Assess designs by looking at the pairwise variances.

Doubling the number of subjects \longrightarrow halving all variances,

so define the **scaled variance** v_{ij} to be

$$\frac{\text{Variance (dose } i - \text{ dose } j) \times \text{number of subjects}}{\sigma^2}.$$

Textbook design

Aim:

- ▶ only doses 0 and k in period k
- ▶ equal replication overall.

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Example: $n = 3, m = 8$

Dose	0	1	2	3
Cohort 1	2	6	0	0
Cohort 2	2	0	6	0
Cohort 3	2	0	0	6

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Cohort 3	2	0	0	6

$$v_{0i} = (n+1)^2$$

$$v_{ij} = 2(n+1)^2$$

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Example: $n = 3, m = 8$

Dose	0	1	2	3
Cohort 1	4	4	0	0
Cohort 2	4	0	4	0
Cohort 3	4	0	0	4

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Example: $n = 3, m = 8$

Dose	0	1	2	3
Cohort 1	4	4	0	0
Cohort 2	4	0	4	0
Cohort 3	4	0	0	4

$$v_{0i} = 4n$$

$$v_{ij} = 8n$$

My proposed “halving” design

Aim:

- ▶ make pairwise variances lower than in other designs, whether or not there are period effects.

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$$s_{ik} = \begin{cases} \frac{m}{2^k} & \text{if } i = 0 \\ \frac{m}{2^{k-i+1}} & \text{if } 0 < i \leq k \\ 0 & \text{otherwise.} \end{cases}$$

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Cohort 1	4	4	0	0
Cohort 2	2	2	4	0
Cohort 3	1	1	2	4

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Example: $n = 3, m = 8$

Dose	0	1	2	3
Cohort 1	4	4	0	0
Cohort 2	2	2	4	0
Cohort 3	1	1	2	4

In Cohort 1: $\frac{m}{2}$ subjects get dose 1; $\frac{m}{2}$ subjects get placebo.

In Cohort i : $\frac{m}{2}$ subjects get dose i ; remaining subjects are allocated as in Cohort $i - 1$ with numbers halved

Calculating variances in the halving design ($n = 3$, $m = 8$)

	Cohort 1								Cohort 2								Cohort 3							
Dose	0	0	0	0	1	1	1	1	0	0	1	1	2	2	2	2	0	1	2	2	3	3	3	3

Calculating variances in the halving design ($n = 3, m = 8$)

	Cohort 1	Cohort 2	Cohort 3
Dose	0 0 0 0 1 1 1 1	0 0 1 1 2 2 2 2	0 1 2 2 3 3 3 3

$\tau_0 + \tau_1 + 2\tau_2 - 4\tau_3$	cohort 1 not estimable	cohort 2 not estimable	cohort 3 estimable
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Calculating variances in the halving design ($n = 3$, $m = 8$)

	Cohort 1	Cohort 2	Cohort 3
Dose	0 0 0 0 1 1 1 1	0 0 1 1 2 2 2 2	0 1 2 2 3 3 3 3
Z_3			+ + + + - - - -

$\tau_0 + \tau_1 + 2\tau_2 - 4\tau_3$	cohort 1 not estimable	cohort 2 not estimable	cohort 3 estimable
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Z_3 is the best linear unbiased estimator of $\tau_0 + \tau_1 + 2\tau_2 - 4\tau_3$.

Calculating variances in the halving design ($n = 3$, $m = 8$)

	Cohort 1	Cohort 2	Cohort 3
Dose	0 0 0 0 1 1 1 1	0 0 1 1 2 2 2 2	0 1 2 2 3 3 3 3
Z_3			+ + + + - - - -

	cohort 1	cohort 2	cohort 3
$\tau_0 + \tau_1 + 2\tau_2 - 4\tau_3$	not estimable	not estimable	estimable
$\tau_0 + \tau_1 - 2\tau_2$	not estimable	orthogonally estimable	

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	Cohort 1	Cohort 2	Cohort 3
Dose	0 0 0 0 1 1 1 1	0 0 1 1 2 2 2 2	0 1 2 2 3 3 3 3
Z_3			+ + + + - - - -
Z_2		+ + + + - - - -	+ + - -

	cohort 1	cohort 2	cohort 3
$\tau_0 + \tau_1 + 2\tau_2 - 4\tau_3$	not estimable	not estimable	estimable
$\tau_0 + \tau_1 - 2\tau_2$	not estimable	orthogonally estimable	

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Z_2 is the best linear unbiased estimator of $\tau_0 + \tau_1 - 2\tau_2$.

Calculating variances in the halving design ($n = 3$, $m = 8$)

	Cohort 1	Cohort 2	Cohort 3
Dose	0 0 0 0 1 1 1 1	0 0 1 1 2 2 2 2	0 1 2 2 3 3 3 3
Z_3			+ + + + - - - -
Z_2		+ + + + - - - -	+ + - -

	cohort 1	cohort 2	cohort 3
$\tau_0 + \tau_1 + 2\tau_2 - 4\tau_3$	not estimable	not estimable	estimable
$\tau_0 + \tau_1 - 2\tau_2$	not estimable	orthogonally estimable	
$\tau_0 - \tau_1$		orthogonally estimable	

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Calculating variances in the halving design ($n = 3, m = 8$)

	Cohort 1	Cohort 2	Cohort 3
Dose	0 0 0 0 1 1 1 1	0 0 1 1 2 2 2 2	0 1 2 2 3 3 3 3
Z_3			+ + + + - - - -
Z_2		+ + + + - - - -	+ + - -
Z_1	+ + + + - - - -	+ + - -	+ -

	cohort 1	cohort 2	cohort 3
$\tau_0 + \tau_1 + 2\tau_2 - 4\tau_3$	not estimable	not estimable	estimable
$\tau_0 + \tau_1 - 2\tau_2$	not estimable	orthogonally estimable	
$\tau_0 - \tau_1$		orthogonally estimable	

Z_3 is the best linear unbiased estimator of $\tau_0 + \tau_1 + 2\tau_2 - 4\tau_3$.

Z_2 is the best linear unbiased estimator of $\tau_0 + \tau_1 - 2\tau_2$.

Z_1 is the best linear unbiased estimator of $\tau_0 - \tau_1$.

Calculating variances in the halving design (continued)

In general, put $Z_j =$
(sum of responses on doses $0, \dots, j-1$ in cohorts j, \dots, n)
– (sum of responses on dose j)

The Z_j are uncorrelated, with known variances.

Linear combinations of them give estimators of all contrasts in the doses.

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The Z_j are uncorrelated, with known variances.

Linear combinations of them give estimators of all contrasts in the doses.

Hence ...

$$\begin{aligned}v_{ij} &= n2^n \left(\sum_{t=i}^{j-1} \frac{1}{f(t)} + \frac{4}{f(j)} \right) && \text{if } 0 < i < j \\v_{0j} &= v_{1j} && \text{if } 1 < j \\v_{01} &= n2^n \frac{4}{f(1)}\end{aligned}$$

where

$$f(j) = 2^{n+1} - 2^j.$$

$$n = 3, m = 8$$

Numbers of subjects

T	Dose	0	1	2	3
	Cohort 1	2	6	0	0
	Cohort 2	2	0	6	0
	Cohort 3	2	0	0	6

S	Dose	0	1	2	3
	Cohort 1	4	4	0	0
	Cohort 2	4	0	4	0
	Cohort 3	4	0	0	4

H	Dose	0	1	2	3
	Cohort 1	4	4	0	0
	Cohort 2	2	2	4	0
	Cohort 3	1	1	2	4

$$n = 3, m = 8$$

Scaled variance of differences

Numbers of subjects

no cohort effect

	Dose	0 1 2 3					1 2 3		
T	Cohort 1	2	6	0	0	0	8.0	8.0	8.0
	Cohort 2	2	0	6	0	1		8.0	8.0
	Cohort 3	2	0	0	6	2			8.0
S	Cohort 1	4	4	0	0	0	8.0	8.0	8.0
	Cohort 2	4	0	4	0	1		12.0	12.0
	Cohort 3	4	0	0	4	2			12.0
H	Cohort 1	4	4	0	0	0	6.9	7.4	9.4
	Cohort 2	2	2	4	0	1		7.4	9.4
	Cohort 3	1	1	2	4	2			10.0

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	Dose	0 1 2 3					1 2 3		
T	Cohort 1	2	6	0	0	0	8.0	8.0	8.0
	Cohort 2	2	0	6	0	1		8.0	8.0
	Cohort 3	2	0	0	6	2			8.0
S	Cohort 1	4	4	0	0	0	8.0	8.0	8.0
	Cohort 2	4	0	4	0	1		12.0	12.0
	Cohort 3	4	0	0	4	2			12.0
H	Cohort 1	4	4	0	0	0	6.9	7.4	9.4
	Cohort 2	2	2	4	0	1		7.4	9.4
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$$n = 3, m = 8$$

Scaled variance of differences

Numbers of subjects

fitting cohort effect

no cohort effect

T	Dose	0	1	2	3		1	2	3		1	2	3
	Cohort 1	2	6	0	0	0	16.0	16.0	16.0	0	8.0	8.0	8.0
	Cohort 2	2	0	6	0	1		32.0	32.0	1		8.0	8.0
	Cohort 3	2	0	0	6	2			32.0	2			8.0
S	Dose	0	1	2	3		1	2	3		1	2	3
	Cohort 1	4	4	0	0	0	12.0	12.0	12.0	0	8.0	8.0	8.0
	Cohort 2	4	0	4	0	1		24.0	24.0	1		12.0	12.0
	Cohort 3	4	0	0	4	2			24.0	2			12.0
H	Dose	0	1	2	3		1	2	3		1	2	3
	Cohort 1	4	4	0	0	0	6.9	9.7	15.7	0	6.9	7.4	9.4
	Cohort 2	2	2	4	0	1		9.7	15.7	1		7.4	9.4
	Cohort 3	1	1	2	4	2			14.0	2			10.0

$$n = 3, m = 8$$

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	Dose	0	1	2	3		1	2	3		1	2	3
T	Cohort 1	2	6	0	0	0	16.0	16.0	16.0	0	8.0	8.0	8.0
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How do we calculate variance?

$$r_i = \text{replication of dose } i = \sum_k s_{ik}$$

$$\lambda_{ij} = \text{concurrence of } i \text{ and } j \text{ in cohorts} = \sum_k s_{ik}s_{jk}$$

$$\mathbf{R} = \text{diag}(r_i) \quad \Lambda = [\lambda_{ij}] \quad \mathbf{L} = \text{information matrix} = \mathbf{R} - m^{-1}\Lambda$$

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Feasible if the eigenvectors are “nice” and there are few distinct eigenvalues.
- ▶ *Ad hoc* methods for special patterns.

Dose-escalation trials: extended designs

There are n doses, with dose $1 < \text{dose } 2 < \dots < \text{dose } n$.

0 denotes the placebo.

There are $n + 1$ cohorts of m subjects each.

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0 denotes the placebo.

There are $n + 1$ cohorts of m subjects each.

Cohort 1 subjects may receive only dose 1 or placebo.

In Cohort i , for $2 \leq i \leq n$, some subjects receive dose i ;
no subject receives dose j if $j > i$.

In Cohort $n + 1$, any dose, or placebo, may be used.

Maintain overall equal replication in the final cohort.

$$s_{i,n+1} = \frac{m}{n+1} \quad \text{for } i = 0, \dots, n$$

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Example: $n = 4$, $m = 15$

Dose	0	1	2	3	4
Cohort 1	3	12	0	0	0
Cohort 2	3	0	12	0	0
Cohort 3	3	0	0	12	0
Cohort 4	3	0	0	0	12
Cohort 5	3	3	3	3	3

Extended Senn design

In the final cohort,
compensate for the previous over-replication of placebo.

$$s_{i,n+1} = \begin{cases} 0 & \text{if } i = 0 \\ \frac{m}{n} & \text{otherwise} \end{cases}$$

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Example: $n = 4$, $m = 16$

Dose	0	1	2	3	4
Cohort 1	8	8	0	0	0
Cohort 2	8	0	8	0	0
Cohort 3	8	0	0	8	0
Cohort 4	8	0	0	0	8
Cohort 5	0	4	4	4	4

Extended halving design

Repeat the final cohort of the standard halving design, to improve comparisons with the highest dose and achieve equal replication overall.

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Cohort 1	8	8	0	0	0
Cohort 2	4	4	8	0	0
Cohort 3	2	2	4	8	0
Cohort 4	1	1	2	4	8
Cohort 5	1	1	2	4	8

Calculating variance in the extended Senn design ($n = 4$)

Example: $n = 4, m = 16$

Dose	0	1	2	3	4
Cohort 1	8	8	0	0	0
Cohort 2	8	0	8	0	0
Cohort 3	8	0	0	8	0
Cohort 4	8	0	0	0	8
Cohort 5	0	4	4	4	4

Example: $n = 4, m = 4$

Dose	0	1	2	3	4
Cohort 1	2	2	0	0	0
Cohort 2	2	0	2	0	0
Cohort 3	2	0	0	2	0
Cohort 4	2	0	0	0	2
Cohort 5	0	1	1	1	1

Calculating variance in the extended Senn design ($n = 4$)

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Dose	0	1	2	3	4
Cohort 1	8	8	0	0	0
Cohort 2	8	0	8	0	0
Cohort 3	8	0	0	8	0
Cohort 4	8	0	0	0	8
Cohort 5	0	4	4	4	4

Example: $n = 4, m = 4$

Dose	0	1	2	3	4
Cohort 1	2	2	0	0	0
Cohort 2	2	0	2	0	0
Cohort 3	2	0	0	2	0
Cohort 4	2	0	0	0	2
Cohort 5	0	1	1	1	1

$$4\mathbf{L} = \begin{bmatrix} 16 & -4 & -4 & -4 & -4 \\ -4 & 7 & -1 & -1 & -1 \\ -4 & -1 & 7 & -1 & -1 \\ -4 & -1 & -1 & 7 & -1 \\ -4 & -1 & -1 & -1 & 7 \end{bmatrix}$$

Calculating variance in the extended Senn design (contd)

$$4\mathbf{L} = \begin{bmatrix} 16 & -4 & -4 & -4 & -4 \\ -4 & 7 & -1 & -1 & -1 \\ -4 & -1 & 7 & -1 & -1 \\ -4 & -1 & -1 & 7 & -1 \\ -4 & -1 & -1 & -1 & 7 \end{bmatrix}$$

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Put $\mathbf{u} = (4, -1, -1, -1, -1)^\top =$ contrast between dose 0 and the rest.

Put $\mathbf{x} = (0, 1, -1, 0, 0)^\top$ or any other contrast between non-zero doses.

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Then $\mathbf{L}\mathbf{u} = 5\mathbf{u}$ and $\mathbf{L}\mathbf{x} = 2\mathbf{x}$,

Calculating variance in the extended Senn design (contd)

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where $\mathbf{P}_1 =$ the idempotent for contrast \mathbf{u}

and $\mathbf{P}_2 =$ the idempotent for contrasts among the non-zero doses.

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Put $\mathbf{u} = (4, -1, -1, -1, -1)^\top$ = contrast between dose 0 and the rest.

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where \mathbf{P}_1 = the idempotent for contrast \mathbf{u}

and \mathbf{P}_2 = the idempotent for contrasts among the non-zero doses.

$$\mathbf{L}^- = \frac{1}{5}\mathbf{P}_1 + \frac{1}{2}\mathbf{P}_2,$$

Hence pairwise variances can be calculated.

Variances in three extended designs

Textbook design

$$v_{0i} = \frac{(n+1)^2(n+2)}{2n+1}$$

$$v_{ij} = \frac{2(n+1)^3}{2n+1}$$

Senn design

$$v_{0j} = \frac{4(n+1)(4+n^2)}{n(4+n)}$$

$$v_{ij} = \frac{8n(n+1)}{4+n}$$

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Senn design

$$v_{0j} = \frac{4(n+1)(4+n^2)}{n(4+n)}$$

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Halving design

$$v_{ij} = \frac{(4+j-i)(n+1)}{2} \quad \text{if } 0 < i < j$$

$$v_{0j} = v_{1j} \quad \text{if } 1 < j$$

$$v_{01} = 2(n+1)$$

$n = 4$

Scaled variance of differences

design

fitting cohort effect

no cohort effect

		1	2	3	4			1	2	3	4
Textbook	0	16.7	16.7	16.7	16.7	0		10.0	10.0	10.0	10.0
	1		27.8	27.8	27.8	1			10.0	10.0	10.0
	2			27.8	27.8	2				10.0	10.0
	3				27.8	3					10.0
Senn		1	2	3	4			1	2	3	4
	0	12.5	12.5	12.5	12.5	0		9.1	9.1	9.1	9.1
	1		20.0	20.0	20.0	1			13.3	13.3	13.3
	2			20.0	20.0	2				13.3	13.3
Halving	3				20.0	3					13.3
		1	2	3	4			1	2	3	4
	0	10.0	12.5	15.0	17.5	0		10.0	10.0	10.0	10.0
	1		12.5	15.0	17.5	1			10.0	10.0	10.0
Halving	2			12.5	15.0	2				10.0	10.0
	3				12.5	3					10.0

$n = 4$		Scaled variance of differences										
design		fitting cohort effect				av'e		no cohort effect				av'e
		1	2	3	4			1	2	3	4	
Textbook	0	16.7	16.7	16.7	16.7		0	10.0	10.0	10.0	10.0	
	1		27.8	27.8	27.8	23.3	1		10.0	10.0	10.0	10.0
	2			27.8	27.8		2			10.0	10.0	
	3				27.8		3				10.0	
Senn		1	2	3	4			1	2	3	4	
	0	12.5	12.5	12.5	12.5		0	9.1	9.1	9.1	9.1	
	1		20.0	20.0	20.0	17.0	1		13.3	13.3	13.3	11.7
	2			20.0	20.0		2			13.3	13.3	
Halving	3				20.0		3				13.3	
		1	2	3	4			1	2	3	4	
	0	10.0	12.5	15.0	17.5		0	10.0	10.0	10.0	10.0	
	1		12.5	15.0	17.5	14.0	1		10.0	10.0	10.0	10.0
	2			12.5	15.0		2			10.0	10.0	
	3				12.5		3				10.0	

Average pairwise variance

Theorem (Standard)

For a connected design with information matrix \mathbf{L} , the average of the pairwise variances is $2S\sigma^2$, where S is the average of the reciprocals of the non-zero eigenvalues of \mathbf{L} .

Random cohort effects

Now assume that the expectation of the response of a subject who gets dose i in cohort k is τ_i , and that cohort effects are uncorrelated random variables with common variance σ_C^2 .

$$\text{Put } \mathbf{C}_{\alpha\beta} = \begin{cases} 1 & \text{if subjects } \alpha \text{ and } \beta \text{ are in the same cohort} \\ 0 & \text{otherwise.} \end{cases}$$

Then the variance-covariance matrix of the responses is

$$\sigma^2 \left(\mathbf{I} - \frac{1}{m} \mathbf{C} \right) + \sigma^2 \theta^{-1} \frac{1}{m} \mathbf{C}$$

where $\sigma^2 + m\sigma_C^2 = \theta^{-1}\sigma^2$,

so $\theta \in [0, 1]$ with $\theta = 0$ if cohort effects are fixed

$\theta = 1$ if cohort effects are zero.

Average variance when information is combined

If we know the value of θ and combine within-cohort and between-cohort information, then the variance of the contrast $\mathbf{x}^\top \boldsymbol{\tau}$ is $\mathbf{x}^\top (\mathbf{L} + \theta \tilde{\mathbf{L}})^{-1} \mathbf{x} \sigma^2$, where

$$\begin{aligned}\mathbf{L} &= \text{diag}(r_i) - m^{-1} \Lambda \\ \tilde{\mathbf{L}} &= m^{-1} \Lambda - \left(\sum r_i \right)^{-1} [r_i r_j].\end{aligned}$$

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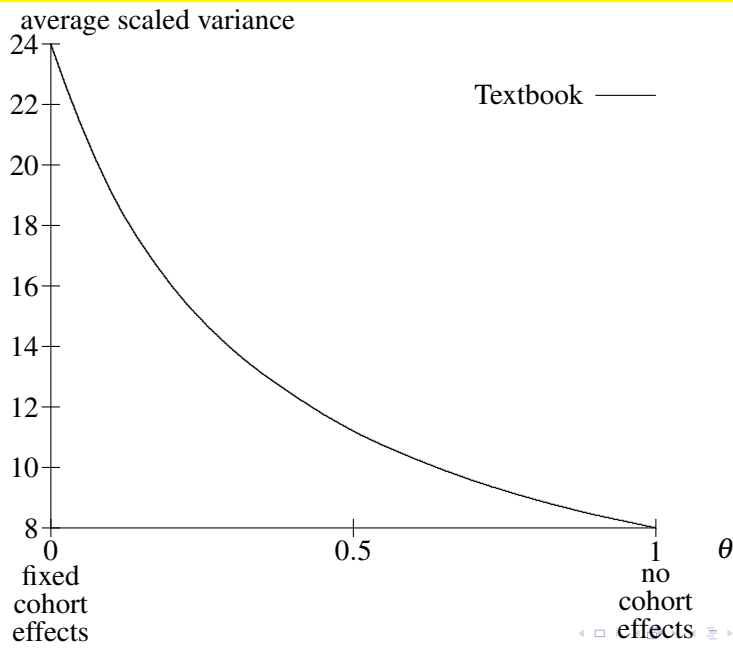
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If \mathbf{L} and \mathbf{L}^- have spectral decompositions $\mathbf{L} = \sum \gamma_i \mathbf{P}_i$ and $\tilde{\mathbf{L}} = \sum \delta_i \mathbf{P}_i$ then the sum of the reciprocals of the eigenvalues of $\mathbf{L} + \theta \tilde{\mathbf{L}}$ is

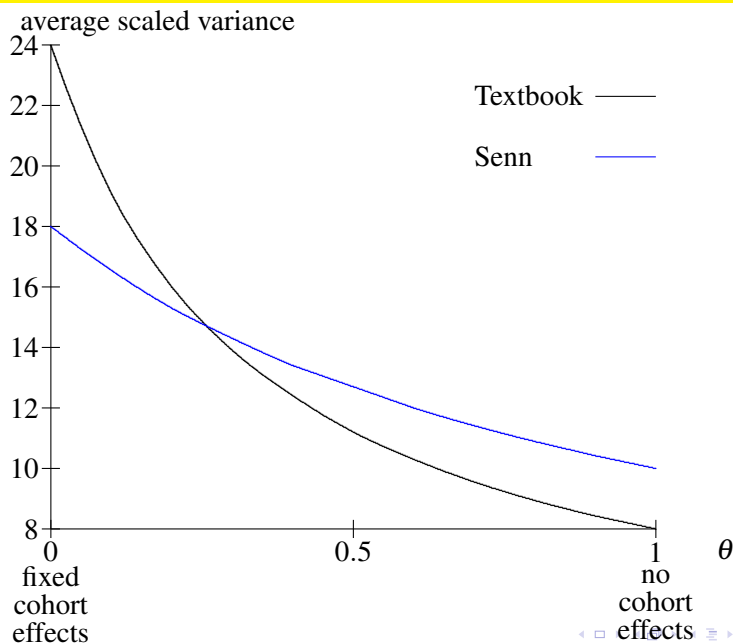
$$\sum \frac{1}{\gamma_i + \theta \delta_i}.$$

Otherwise, the average variance must be computed numerically for each value of θ .

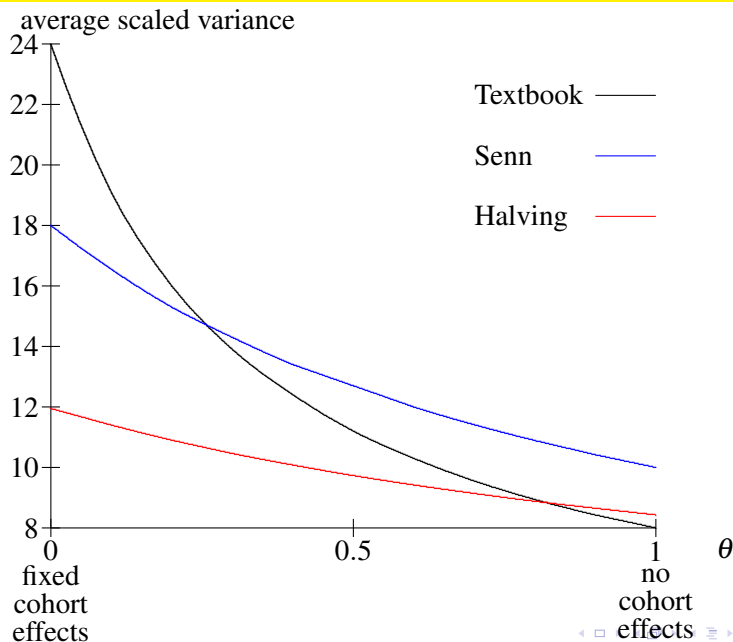
Average variance for 3 doses in 3 cohorts



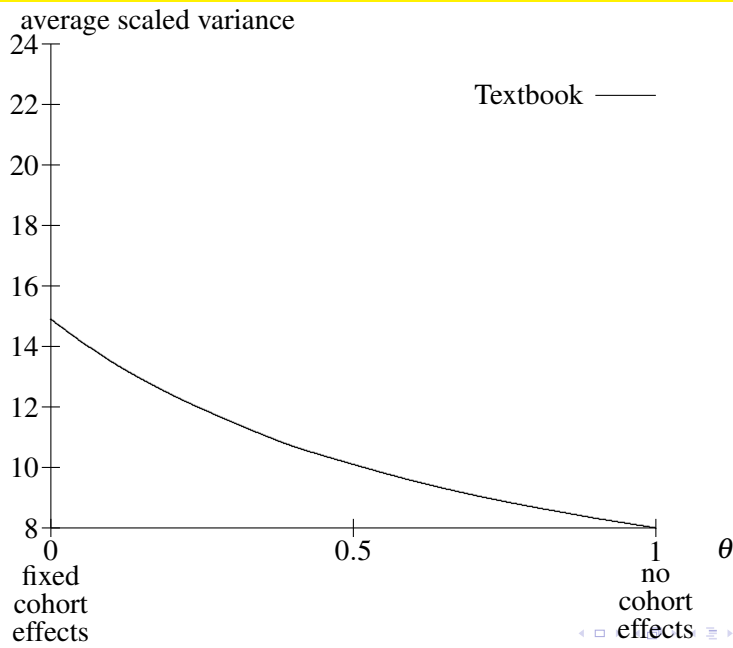
Average variance for 3 doses in 3 cohorts



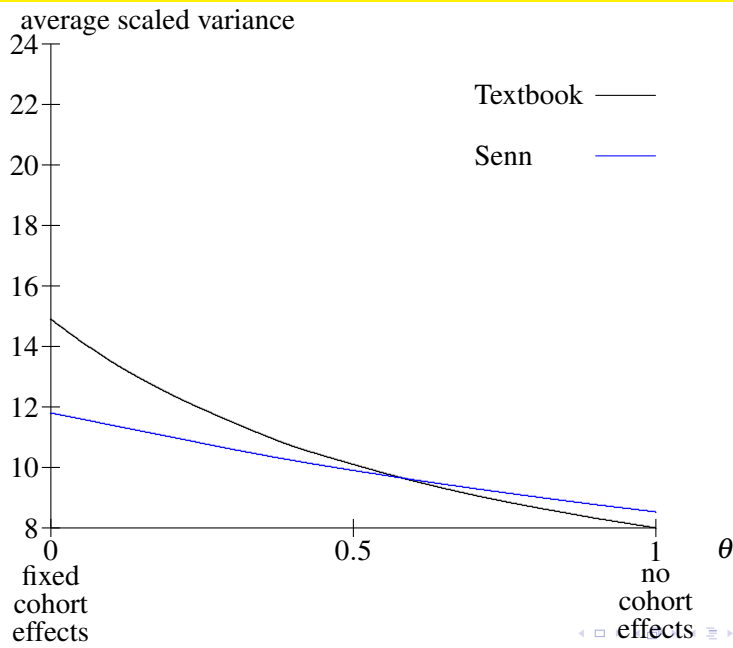
Average variance for 3 doses in 3 cohorts



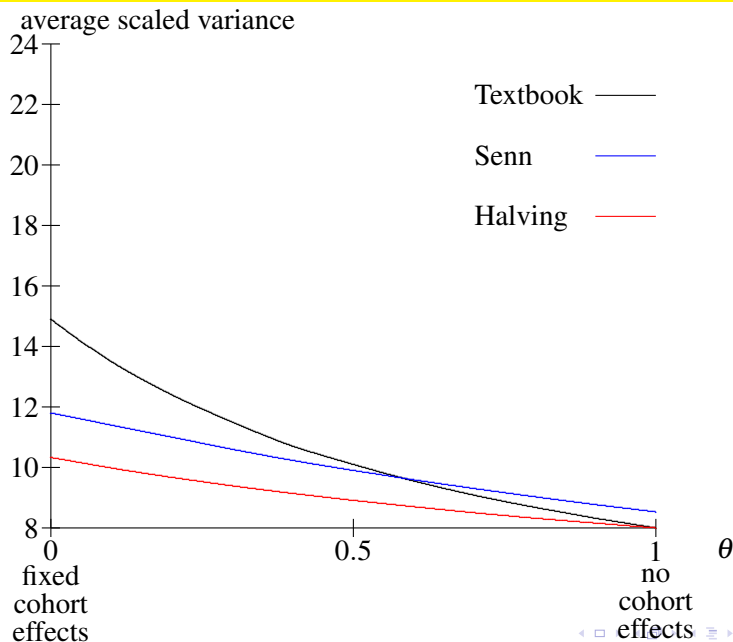
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