





Overview

- 'Classical' sample size estimation in BE
 - Patient's & producer's risk
 - Power in study planning
- History / early approaches
 - Add-on studies
 - Problems with α -inflation
- Uncertainties
 - Variability
 - Test/Reference-ratio
 - Sensitivity analysis





Overview

- Recent developments
 - Review of guidelines
 - Multi-sequential designs
 - Two-stage sequential designs
- Open issues
 - Feasibility / futility rules
 - Arbitrary PE and/or power; adaption for stage 1 PE
 - Dropping a candidate formulation from a higherorder X-over
 - Application to replicated designs (for HVDs/HVDPs)





α - vs. β -Error

- All formal decisions are subjected to two types of error:
 - Error Type I (α -Error, Risk Type I)
 - Error Type II (β -Error, Risk Type II) Example from the justice system:

Verdict	Defendant innocent	Defendant guilty
Presumption of innocence not accepted (guilty)	Error type I	Correct
Presumption of innocence accepted (not guilty)	Correct	Error type II



α - vs. β -Error

Or in more statistical terms:

Decision	Null hypothesis true	Null hypothesis false
Null hypothesis rejected	Error type I	Correct (H _a)
Failed to reject null hypothesis	Correct (H ₀)	Error type II

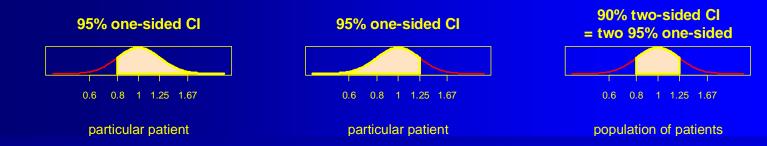
•In BE-testing the null hypothesis is bioinequivalence $(\mu_1 \neq \mu_2)!$

Decision	Null hypothesis true	Null hypothesis false		
Null hypothesis rejected	Patients' risk	Correct (BE)		
Failed to reject null hypothesis	Correct (not BE)	Producer's risk		



α- vs. β-Error

- α -Error: Patient's Risk to be treated with a bioinequivalent formulation (H_0 falsely rejected)
 - BA of the test compared to reference in a *particular* patient is risky *either* below 80% *or* above 125%.
 - If we keep the risk of particular patients at 0.05 (5%), the risk of the entire population of patients (<80% and >125%) is $2\times\alpha$ (10%) expressed as: 90% CI = $1-2\times\alpha=0.90$







α - vs. β -Error

- β-Error: Producer's Risk to get no approval for a bioequivalent formulation (H₀ falsely not rejected)
 - Set in study planning to ≤ 0.2 , where power = $1 \beta = \geq 80\%$
 - ■If power is set to 80 %

One out of five studies will fail just by chance!

α 0.05	BE
not BE	β 0.20

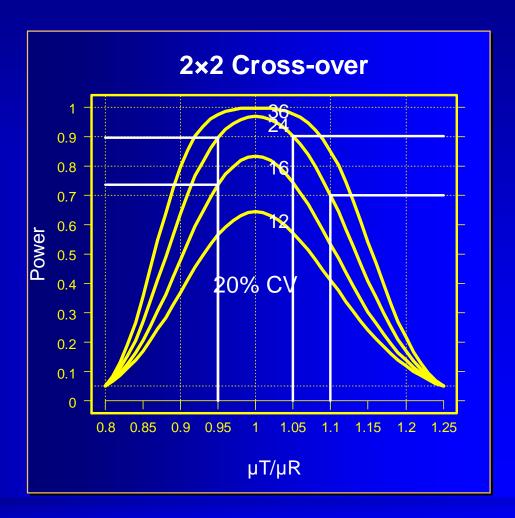


Power Curves

Power to show BE with 12 – 36 subjects for CV_{intra} 20%

n 24 \downarrow 16: power $0.896 \rightarrow 0.735$

 μ_T/μ_R 1.05 \downarrow 1.10: power 0.903 \rightarrow 0.700





Power vs. Sample Size

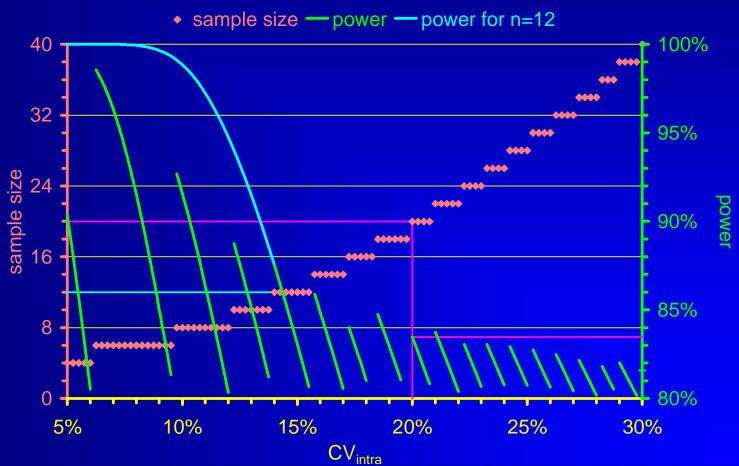
- It is not possible to calculate the required sample size directly.
- Power is calculated instead; the smallest sample size which fulfills the minimum target power is used.
 - Example: α 0.05, target power 80% (β 0.2), T/R 0.95, CV_{intra} 20% \rightarrow minimum sample size 19 (power 81%), rounded up to the next even number in a 2×2 study (power 83%).

n	power
16	73.54%
17	76.51%
18	79.12%
19	81.43%
20	83.47%



Power vs. Sample Size

2x2 cross-over, T/R 0.95, AR 80-125%, target power 80%





Tools

- Sample Size Tables (Phillips, Diletti, Hauschke, Chow, Julious, ...)
- Approximations (Diletti, Chow, Julious, ...)
- General purpose (SAS, S+, R, StaTable, ...)
- Specialized Software (nQuery Advisor, PASS, FARTSSIE, StudySize, ...)
- Exact method (Owen implemented in R-package PowerTOST)*
 - * Thanks to Detlew Labes!





Background

- Reminder: Sample Size is not directly obtained; only power
- Solution given by DB Owen (1965) as a difference of two bivariate noncentral t-distributions
 - Definite integrals cannot be solved in closed form
 - "Exact' methods rely on numerical methods (currently the most advanced is AS 243 of RV Lenth; implemented in R, FARTSSIE, EFG). nQuery uses an earlier version (AS 184).





Background

- Power calculations...
 - "Brute force' methods (also called 'resampling' or 'Monte Carlo') converge asymptotically to the true power; need a good random number generator (*e.g.*, Mersenne Twister) and may be time-consuming
 - 'Asymptotic' methods use large sample approximations
 - Approximations provide algorithms which should converge to the desired power based on the t-distribution



Comparison

CV/0/		
1 -1/0/		

original values	Method	Algorithm	5	7.5	10	12	12.5	14	15	16	17.5	18	20	22
PowerTOST 0.8-2 (2011)	exact	Owen's Q	4	6	8	8	10	12	12	14	16	16	20	22
Patterson & Jones (2006)	noncentr. t	AS 243	4	5	7	8	9	11	12	13	15	16	19	22
Diletti et al. (1991)	noncentr. t	Owen's Q	4	5	7	NA	9	NA	12	NA	15	NA	19	NA
nQuery Advisor 7 (2007)	noncentr. t	AS 184	4	6	8	8	10	12	12	14	16	16	20	22
FARTSSIE 1.6 (2008)	noncentr. t	AS 243	4	5	7	8	9	11	12	13	15	16	19	22
EFG 2.01 (2009)	noncentr. t	AS 243	4	5	7	8	9	11	12	13	15	16	19	22
EFG 2:01 (2009)	brute force	ElMaestro	4	5	7	8	9	11	12	13	15	16	19	22
StudySize 2.0.1 (2006)	central t	?	NA	5	7	8	9	11	12	13	15	16	19	22
Hauschke et al. (1992)	approx. t		NA	NA	8	8	10	12	12	14	16	16	20	22
Chow & Wang (2001)	approx. t		NA	6	6	8	8	10	12	12	14	16	18	22
Kieser & Hauschke (1999)	approx. t		2	NA	6	8	NA	10	12	14	NA	16	20	24

CV%

original values	Method	Algorithm	22.5	24	25	26	27.5	28	30	32	34	36	38	40
PowerTOST 0.8-2 (2011)	exact	Owen's Q	24	26	28	30	34	34	40	44	50	54	60	66
Patterson & Jones (2006)	noncentr. t	AS 243	23	26	28	30	33	34	39	44	49	54	60	66
Diletti et al. (1991)	noncentr. t	Owen's Q	23	NA	28	NA	33	NA	39	NA	NA	NA	NA	NA
nQuery Advisor 7 (2007)	noncentr. t	AS 184	24	26	28	30	34	34	40	44	50	54	60	66
FARTSSIE 1.6 (2008)	noncentr. t	AS 243	23	26	28	30	33	34	39	44	49	54	60	66
EFG 2.01 (2009)	noncentr. t	AS 243	23	26	28	30	33	34	39	44	49	54	60	66
Li G 2.01 (2009)	brute force	ElMaestro	23	26	28	30	33	34	39	44	49	54	60	66
StudySize 2.0.1 (2006)	central t	?	23	26	28	30	33	34	39	44	49	54	60	66
Hauschke et al. (1992)	approx. t		24	26	28	30	34	36	40	46	50	56	64	70
Chow & Wang (2001)	approx. t		24	26	28	30	34	34	38	44	50	56	62	68
Kieser & Hauschke (1999)	approx. t		NA	28	30	32	NA	38	42	48	54	60	66	74



Approximations

Hauschke et al. (1992)

```
Patient's risk \alpha 0.05. Power 80% (Producer's risk \beta
   0.2), AR [0.80 - 1.25], CV 0.2 (20\%), T/R 0.95
1. \Delta = \ln(0.8) - \ln(T/R) = -0.1719
2. Start with e.g. n=8/sequence
      1. df = n \cdot 2 - 1 = 8 \times 2 - 1 = 14
      2. t_{\alpha,df} = 1.7613
      3. t_{\beta,df} = 0.8681
      4. new n = [(t_{\alpha,df} + t_{\beta,df})^2 \cdot (CV/\Delta)]^2 =
          (1.7613+0.8681)^2 \times (-0.2/0.1719)^2 = 9.3580
3. Continue with n=9.3580/sequence (N=18.716 \rightarrow 19)
      1. df = 16.716; roundup to the next integer 17
      2. t_{\alpha,df} = 1.7396
      3. t_{\beta,df} = 0.8633
      4. new n = [(t_{\alpha,df} + t_{\beta,df})^2 \cdot (CV/\Delta)]^2 =
          (1.7396+0.8633)^2 \times (-0.2/0.1719)^2 = 9.1711
4. Continue with n=9.1711/sequence (N=18.3422 \rightarrow 19)
      1. df = 17.342; roundup to the next integer 18
      2. t_{\alpha,df} = 1.7341
      3. t_{\beta,df} = 0.8620
      4. new n = [(t_{\alpha,df} + t_{\beta,df})^2 \cdot (CV/\Delta)]^2 =
```

 $(1.7341+0.8620)^2 \times (-0.2/0.1719)^2 = 9.1233$

5. Convergence reached (N=18.2466 \rightarrow 19): Use 10 subjects/sequence (20 total)

S-C Chow and H Wang (2001)

```
Patient's risk \alpha 0.05. Power 80% (Producer's risk \beta
   0.2), AR [0.80 - 1.25], CV 0.2 (20\%), T/R 0.95
1. \Delta = \ln(T/R) - \ln(1.25) = 0.1719
2. Start with e.g. n=8/sequence
       1. df_{\alpha} = roundup(2 \cdot n-2) \cdot 2-2 = (2 \times 8-2) \times 2-2 = 26
       2. df_8 = roundup(4 \cdot n-2) = 4 \times 8-2 = 30
       3. t_{\alpha,df} = 1.7056
       4. t_{B/2,df} = 0.8538
       5. new n = \beta^2 \cdot [(t_{\alpha,df} + t_{\beta/2,df})^2/\Delta^2] =
          0.2^2 \times (1.7056+0.8538)^2 / 0.1719^2 = 8.8723
3. Continue with n=8.8723/sequence (N=17.7446 \rightarrow 18)
       1. df_{\alpha} = roundup(2 \cdot n-2) \cdot 2-2=(2 \times 8.8723-2) \times 2-2 = 30
       2. df_8 = roundup(4 \cdot n-2) = 4 \times 8.8723-2 = 34
       3. t_{\alpha, df} = 1.6973
       4. t_{\beta/2,df} = 0.8523
       5. new n = \beta^2 \cdot [(t_{\alpha,df} + t_{\beta/2,df})^2/\Delta^2] =
          0.2^2 \times (1.6973 + 0.8538)^2 / 0.1719^2 = 8.8045
```

sample size	18	19	20		
power %	79.124	81.428	83.468		

4. Convergence reached (N=17.6090 \rightarrow 18):

Use 9 subjects/sequence (18 total)





Approximations obsolete

- Exact sample size tables still useful in checking the plausibility of software's results
- Approximations based on noncentral t (FARTSSIE17)



http://individual.utoronto.ca/ddubins/FARTSSIE17.xls

or
$$\mathbb{R} / S+ \rightarrow$$

Exact method (Owen) in R-package PowerTOST

```
http://cran.r-project.org/web/packages/PowerTOST/
```

```
require(PowerTOST)
  sampleN.TOST(alpha = 0.05,
  targetpower = 0.80, logscale = TRUE,
  theta1 = 0.80, diff = 0.95, CV = 0.30,
  design = "2x2", exact = TRUE)
```

```
alpha
        <- 0.05
                     # alpha
        <- 0.30
                     # intra-subject CV
CV
theta1 <- 0.80
                     # lower acceptance limit
theta2 <- 1/theta1 # upper acceptance limit
                     # expected ratio T/R
ratio
        <- 0.95
PwrNeed <- 0.80
                     # minimum power
Limit
        <- 1000
                     # Upper Limit for Search
                     # start value of sample size search
        <- 4
        <- sqrt(2)*sqrt(log(CV^2+1))
repeat{
        \leftarrow qt(1-alpha,n-2)
 nc1
        <- sqrt(n)*(log(ratio)-log(theta1))/s
        <- sqrt(n)*(log(ratio)-log(theta2))/s
  prob1 \leftarrow pt(+t,n-2,nc1); prob2 \leftarrow pt(-t,n-2,nc2)
  power <- prob2-prob1
                     # increment sample size
  if(power >= PwrNeed | (n-2) >= Limit) break }
       <- n-2
if(Total == Limit){
  cat("Search stopped at Limit", Limit,
        obtained Power", power*100, "%\n")
  cat("Sample Size", Total, "(Power", power*100, "%) \n")
```



- Sometimes properly planned studies fail due to
 - Pure chance (producer's risk hit)
 - False assumptions about variability and/or T/R-ratio
 - Poor study conduct (increasing variability)
 - 'True' bioinequivalence
- The patient's risk must be preserved
 - Already noticed at Bio-International Conferences (1989, 1992) and guidelines from the 1990s





- The primary concern in bioequivalence assessment is to limit the risk of erroneously accepting bioequivalence. Only statistical procedures which do not exceed the nominal risk of 5% can be approved, and among them the one with the smallest risk of erroneously rejecting bioequivalence should be selected.'*
- Performing a second study and pooling data with the first's not acceptable
- Performing a (much larger) second study and base BE on this study alone was (and is) acceptable
 - * CPMP Working Party
 Investigation of Bioavailability and Bioequivalence: Note for Guidance
 Section 3.6 Data analysis, Document Ref. III/54/89-EN (1 May 1992)





- Inflation/preservation of patient's risk
 - Repeated tests increase the overall significance level. For two tests the overall level is ~ 8%¹
 - ■With two repeated tests at 2.94% overall $\alpha \sim 5\%^2$
 - Derived for tests assuming normally distributed data with known variances. Approximately valid if sample size not too small.
 - Armitage P, McPherson K, and BC Rowe Repeated significance tests on accumulating data J R Statist Soc A 132, 235–44 (1969)
 - ² SJ Pocock Group sequential methods in the design and analysis of clinical trials Biometrika 64, 191–9 (1977)





- •However naïve pooling (*without* α -adjustment) was performed in the past
 - Statistical model modified in order to include a formulation-by-study interaction factor.
 - Test for homogeneity of error variances between studies
 - Pooling only acceptable if both tests not significant*
 - * H Mellander

Problems and Possibilities with the Add-On Subject Design, in: Midha KK, Blume HH (eds.)
Bio-International. Bioavailability, Bioequivalence and Pharmacokinetics medpharm Scientific Publishers, Stuttgart, pp. 85–90 (1993)





Add-on Design

- According to Canadian guidances (1992+)
 - Pooling of two or more [sic!] studies may be allowed
 - Model:

```
Study + Subject(Study) + Period(Study) +
Treatment + Treatment × Study
```

- Consistency tests
 - Test for equality of residual mean squares: Ratios of MSE of the 1st study to all others; smaller value used as denominator. F-test at 5%.
 - Formulation-by-study interaction. *F*-test at 5%.
 - If both tests not significant, pooling without (!) α -adjustment

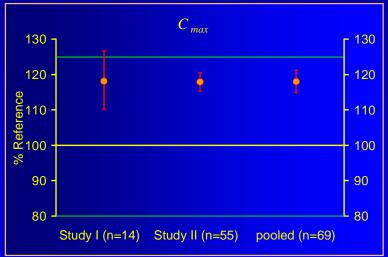




Add-on Design

• Example (C_{max} , SD fasting studies)

Study	1	П	pooled
n	14	55	69
PE%	118.14	117.93	118.04
CI%	110.16	115.40	114.91
	126.70	120.53	121.25
MSE	0.01078	0.004645	0.005777
CV _{intra}	10.41	6.82	7.61



- ■MSE-ratio 2.3198: $p(F_{12.53})$ 0.01812
- Study-by-formulation interaction: $p(F_{1.65})$ 0.9573
- Pooling not allowed due to lacking equality of MSEs



Problems with α -inflation

- Patient's risk likely is not preserved
 - The probability to obtain at least one significant result with k independent (!) t-tests (at level α) is

$$P(k) = 1 - (1 - \alpha)^{k}$$

 $P(2) = 1 - (1 - 0.05)^{2} = 0.0975$

 Bonferroni-correction for two studies would mandate calculation of a 95% confidence interval

$$\alpha_{adj} = \alpha/k$$

$$P_{adi}(2) = 1 - (1 - 0.025)^2 = 0.04938 < 0.05$$

Applicability doubtful since no independent tests!





Problems with α -inflation

- Patient's risk (cont'd)
 - ■For two repeated tests on accumulating data the overall level is ~8% (Armitage 1969)
 - ■In naïve pooling the variance will be underestimated¹
 - Simulations of BE studies (sample sizes 24 48, CV_{intra} 19 37%, 1 3 interim looks, Lan-DeMets sequential method, 1540 studies in all combinations) showed empirical α of up to $5.97\%^2$
 - Wittes J, Schabenberger O, Zucker D, Brittain E, and M Proschan Internal pilot studies I: type I error rate of the naïve t-test Statistics in Medicine 18, 3481–91 (1999)
 - ² Hauck WW, Preston PE, and FY Bois A group sequential approach to crossover trials for average bioequivalence Journal of Biopharmaceutical Statistics 7(1), 87–96 (1997)





Problems with α -inflation

- Patient's risk (cont'd)
 - Simulations of 1 Mio BE studies (12 subjects in 1st study, CV_{intra} 20%, sample size re-estimation based on PE 0.95 and CV_{intra} of 1st study) showed empirical α of 5.84%*
 - Naïve pooling without α -adjustment (Add-on designs, internal pilot designs) should be avoided!

* Potvin D, Diliberti CE, Hauck WW, Parr AF, Schuirmann DJ, and RA Smith Sequential design approaches for bioequivalence studies with crossover designs Pharmaceut Statist 7/4, 245–62 (2008), DOI: 10.1002/pst.294 http://www3.interscience.wiley.com/cgi-bin/abstract/115805765/ABSTRACT





Uncertainties

- CV_{intra} used in sample size estimation is not set in stone but an *estimate*!
 - ■Sample sizes for target power 90%, PE 0.95, CV_{intra} 20% → n=26
 - Not done yet!
 What if CV_{intra} ≠ 20%?

CV _{intra}	n	power _n	power _{n=26}
15	16	0.92602	0.99153
16	18	0.92685	0.98379
17	20	0.92601	0.97253
18	22	0.92400	0.95763
19	24	0.92114	0.93922
20	26	0.91763	0.91763
21	28	0.91362	0.89329
22	30	0.90919	0.86659
23	32	0.90443	0.83794
24	36	0.91451	0.80767
25	38	0.90889	0.77606



Uncertainties

 According to 2010 GL test and reference batches should not differ in measured content

by
$$>\pm5\%$$

- n=26, CV_{intra} 20%, PE 0.95
 - → power 91.76%
- What about analytical error?

PE	power
0.90	0.66945
0.91	0.73684
0.92	0.79577
0.93	0.84547
0.94	0.88591
0.95	0.91763
0.96	0.94154
0.97	0.95867
0.98	0.97003
0.99	0.97646
1.00	0.97853

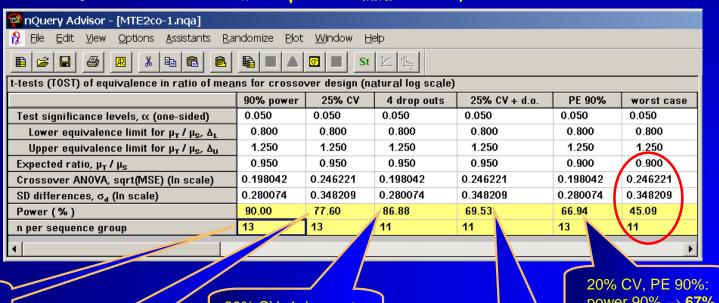


- •ICH E9 (1998)
 - Section 3.5 Sample Size, paragraph 3
 - The method by which the sample size is calculated should be given in the protocol [...]. The basis of these estimates should also be given.
 - It is important to investigate the sensitivity of the sample size estimate to a variety of deviations from these assumptions and this may be facilitated by providing a range of sample sizes appropriate for a reasonable range of deviations from assumptions.
 - In confirmatory trials, assumptions should normally be based on published data or on the results of earlier trials.





Example nQuery Advisor: $\sigma_{w} = \sqrt{\ln(CV_{intra}^{2} + 1)}; \sqrt{\ln(0.2^{2} + 1)} = 0.198042$



20% CV: n = 26

25% CV: power $90\% \rightarrow 78\%$ 20% CV, 4 drop outs: power $90\% \rightarrow 87\%$

25% CV, 4 drop outs: power $90\% \rightarrow 70\%$

power 90% \rightarrow 67%



Example

PowerTOST, function sampleN.TOST





 To calculate Power for a given sample size, use function power. TOST

```
require(PowerTost)
power.TOST(alpha=0.05, logscale=TRUE, theta1=0.8, theta2=1.25,
           theta0=0.95, CV=0.25, n=26, design="2x2", exact=TRUE)
[1] 0.7760553
power.TOST(alpha=0.05, logscale=TRUE, theta1=0.8, theta2=1.25,
           theta0=0.95, CV=0.20, n=22, design="2x2", exact=TRUE)
[1] 0.8688866
power.TOST(alpha=0.05, logscale=TRUE, theta1=0.8, theta2=1.25,
           theta0=0.95, CV=0.25, n=22, design="2x2", exact=TRUE)
[1] 0.6953401
power.TOST(alpha=0.05, logscale=TRUE, theta1=0.8, theta2=1.25,
           theta0=0.90, CV=0.20, n=26, design="2x2", exact=TRUE)
[1] 0.6694514
power.TOST(alpha=0.05, logscale=TRUE, theta1=0.8, theta2=1.25,
           theta0=0.90, CV=0.25, n=22, design="2x2", exact=TRUE)
[1] 0.4509864
```





- Must be done before the study (a priori)
- The Myth of retrospective (a posteriori or post hoc) Power...
 - High values do not further support the claim of already demonstrated bioequivalence.
 - Low values do not invalidate a bioequivalent formulation.
 - Further reader:

RV Lenth

Two Sample-Size Practices that I don't recommend (2000)

JM Hoenig and DM Heisey

The Abuse of Power: The Pervasive Fallacy of Power Calculations for Data Analysis (2001)

P Bacchetti

Current sample size conventions: Flaws, harms, and alternatives (2010)





The Myth of Power

There is simple intuition behind results like these: If my car made it to the top of the hill, then it is powerful enough to climb that hill; if it didn't, then it obviously isn't powerful enough. Retrospective power is an obvious answer to a rather uninteresting question. A more meaningful question is to ask whether the car is powerful enough to climb a particular hill never climbed before; or whether a different car can climb that new hill. Such questions are prospective, not retrospective.

The fact that retrospective power adds no new information is harmless in its own right. However, in typical practice, it is used



to exaggerate the validity of a significant result ("not only is it significant, but the test is really powerful!"), or to make excuses for a nonsignificant one ("well, P is .38, but that's only because the test isn't very powerful"). The latter case is like blaming the messenger.

RV Lenth

Two Sample-Size Practices that I don't recommend http://www.math.uiowa.edu/~rlenth/Power/2badHabits.pdf





Recent developments

- Review of guidelines
 - ■WHO (May 2006)
 - Add-on studies
 - Declared in the protocol
 - Appropriate statistical treatment
 - Japanese GL given as an example
 - South Africa (Jul 2007)
 - Add-on studies
 - Declared in the protocol
 - Maximum sample size a priori
 - No recommendations about statistical analysis





Recent developments

- Review of guidelines
 - Japan (Nov 2006); no essential change to Dec 1997
 - Add-on studies
 - Sample size at least 50% of 1st study
 - 'Study' as a factor in the analysis
 - No consistency tests
 - No Bonferroni-correction
 - If sample size of 1st study ≥20 or sample size of pooled studies ≥30 BE may be assessed on PE (within 0.90 – 1.11) and dissolution similarity (no CI)
 - Argentina (Sep 2006, Mar 3007)
 - Sequential Designs: not statisticals details





Recent developments

- Review of guidelines
 - New Zealand (Oct 2001)
 - Sequential Designs
 - Declared in the protocol
 - Maximum sample size a priori (≤40!)
 - 'Appropriate statistical tests (e.g., sequential t-test)'

FDA

- Sequential Designs: not mentioned in guidances but acceptable (pers. comm. Barbara Davit, May 2010)
- EMA (Jan 2010)
 - Sequential Designs: fairly detailed informations given



Two-Stage Design

- EMA GL on BE (2010)
 - Section 4.1.8
 - Initial group of subjects treated and data analysed.
 - If BE not been demonstrated an additional group can be recruited and the results from both groups combined in a final analysis.
 - Appropriate steps to preserve the overall type I error (patient's risk).
 - Stopping criteria should be defined a priori.
 - First stage data should be treated as an interim analysis.





Two-Stage Design

- EMA GL on BE (2010)
 - Section 4.1.8 (cont'd)
 - Both analyses conducted at adjusted significance levels (with the confidence intervals accordingly using an adjusted coverage probability which will be higher than 90%). [...] 94.12% confidence intervals for both the analysis of stage 1 and the combined data from stage 1 and stage 2 would be acceptable, but there are many acceptable alternatives and the choice of how much alpha to spend at the interim analysis is at the company's discretion.



Two-Stage Design

- EMA GL on BE (2010)
 - Section 4.1.8 (cont'd)
 - Plan to use a two-stage approach must be prespecified in the protocol along with the adjusted significance levels to be used for each of the analyses.
 - When analysing the combined data from the two stages, a term for stage should be included in the ANOVA model.



Classification

I. Fixed sample design (conventional BE)

IIa. Two-stage sample size recalculation using the variance only

Ilb. Multi-stage sample size recalculation using the variance only

IIc. Group sequential trials that monitor variance to recalculate sample size and the treatment difference to permit early stopping

IIIa. Two-stage sample size recalculation using the variance and original treatment difference for conditional power

IIIb. Two-stage sample size recalculation using the variance and observed treatment difference

IIIc. Multi-stage sample size recalculation using the variance and treatment difference to permit early stopping

Schwartz TA and JS Denne

Common threads between sample size recalculation and group sequential procedures

Pharmaceut. Statist. 2, 263-71 (2003)





Sequential Designs

- Have a long and accepted tradition in clinical research (mainly phase III)
 - Based on work by Armitage *et al.* (1969), McPherson (1974), Pocock (1977), O'Brien and Fleming (1979), Lan & DeMets (1983), ...
 - First proposal by Gould (1995) in the area of BE did not get regulatory acceptance in Europe, but
 - stated in Canadian draft guidance (2010) and EMA's BE guideline (2010).

AL Gould

Group Sequential Extension of a Standard Bioequivalence Testing Procedure J Pharmacokin Biopharm 23/1, 57–86 (1995)





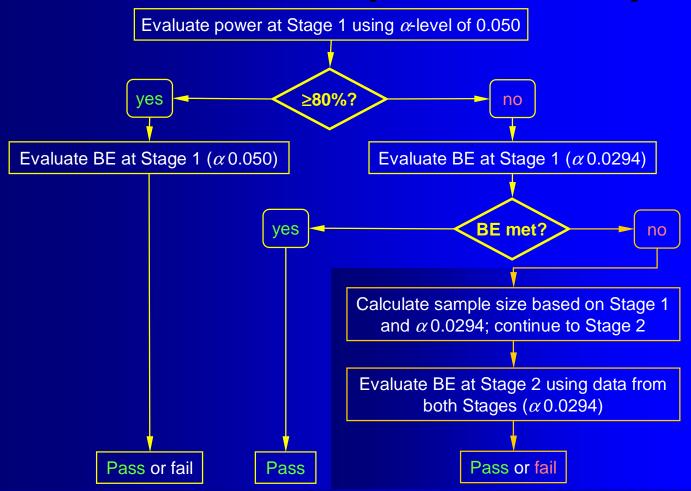
Sequential Designs

- Methods by Potvin et al. (2008) promising
 - Supported by 'The Product Quality Research Institute' (members: FDA/CDER, Health Canada, USP, AAPS, PhRMA, ...)
 - Acceptable by US-FDA
 - Canada? Or Gould (1995) mandatory?
 - Acceptable as a Two-Stage Design in the EU
 - Three of BEBAC's protocols already approved by German BfArM

Potvin D, Diliberti CE, Hauck WW, Parr AF, Schuirmann DJ, and RA Smith Sequential design approaches for bioequivalence studies with crossover designs Pharmaceut Statist 7/4, 245–62 (2008), DOI: 10.1002/pst.294 http://www3.interscience.wiley.com/cgi-bin/abstract/115805765/ABSTRACT









- Technical Aspects
 - Only one Interim Analysis (after Stage 1)
 - If possible, use software (too wide step sizes in Diletti's tables), preferrable the exact method (avoid approximations)
 - Should be termed 'Power Analysis' *not* 'Bioequivalence Assessment' in the protocol
 - No a-posteriori Power only a validated method in the decision tree
 - No adjustment for the PE observed in Stage 1





- Technical Aspects (cont'd)
 - No stop criterion ('futility rule') preventing to go into Stage 2 with a very high sample size! Must be clearly stated in the protocol (unfamiliar to the IEC because common in Phase III)
 - If power <80% in Stage 1 or in the pooled analysis (data from Stages 1 + 2), Pocock's α 0.0294 is used (*i.e.*, the 1 2× α = 94.12% Cl is calculated)
 - Overall patient's risk preserved at ~≤0.05





- Technical Aspects (cont'd)
 - If the study is stopped after Stage 1, the (conventional) statistical model is:

```
fixed: sequence + period + treatment
random: subject(sequence)
```

If the study continues to Stage 2, the model for the combined analysis is:

```
fixed: sequence + stage + period(stage) + treatment
random: subject(sequence × stage)
```

- No poolability criterion; combining is always allowed
 - even for significant differences between Stages



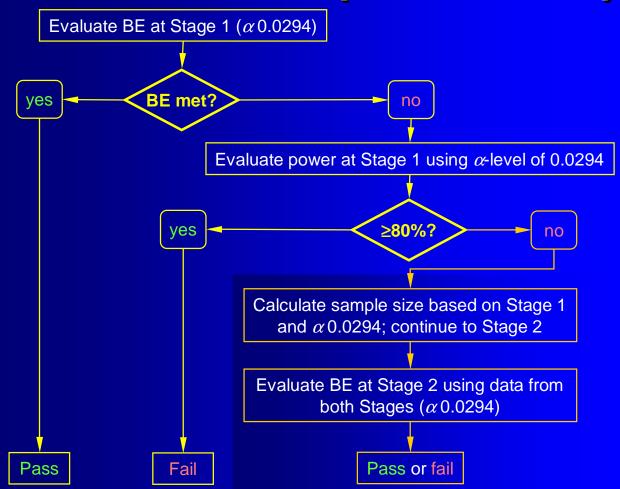


- Technical Aspects (cont'd)
 - Potvin et al. used a simple approximative power estimation based on the shifted t-distribution (to increase speed in their simulations?)
 - If possible use the exact method (Owen; package PowerTOST exact = TRUE) or at least the one based on the noncentral t-distribution (PowerTOST exact = FALSE)
 - Power obtained in Stage 1:

method	power
approx. (shifted t)	64.94%
approx. (noncentral t)	66.45%
exact	66.47%









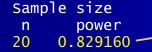
Potvin et al. (example B/C)

```
Model Specification and User Settings
                                                              12 subjects in Stage 1,
       Dependent variable : Response
                                                              conventional BE model
                Transform: LN
              Fixed terms : int+Sequence+Treatment+Period
    Random/repeated terms : Sequence*Subject
Final variance parameter estimates:
   Var(Sequence*Subject)
                              0.408682
                                                CV<sub>intra</sub> 18.2%
            Var(Residual)
                              0.0326336
          Intrasubject CV
                             0.182132
                                                                     \alpha 0.0294
Bioequivalence Statistics
                                                                     (if power < 80%)
User-Specified Confidence Level for CI's = 94.1200
Percent of Reference to Detect for 2-1 Tests = 20.0%
A.H.Lower = 0.800 A.H.Upper = 1.250
                       LSMean= 0.954668
Reference: Reference
                                          SE = 0.191772
                                                         GeoLSM=
                                                                    2.597808
                       LSMean= 1.038626
                                          SE= 0.191772
                                                                    2.825331
Test:
          Test
                                                         GeoLSM=
    Difference =
                      0.0840.
                               Diff_SE=
                                           0.0737, df = 10.0
    Ratio(%Ref) =
                    108.7583
                                                    Failed 90% CI (if power ≥80%)
                      Classical
                                                    and 94.12% CI (if power <80%)
      90% = (
                  95.1474, 124.3162)
                92.9291, 127.2838)
   CI User = (
    Failed to show average bioequivalence for confidence=94.12 and percent=20.0.
```



Potvin et al. (example B/C)

```
\alpha 0.05 (C), \alpha 0.0294 (B), expected
require(PowerTOST)
                                                    ratio 95% – not 108.76% obs. in
power.TOST(alpha=0.05, logscale=TRUE,
                                                    stage 1! CV<sub>intra</sub> 18.2%, 12 subjects
           theta1=0.8, theta2=1.25, theta0=0.95.
           CV=0.182132, n=12.
                                                    in Stage 1
           design = "2x2", exact = TRUE)
                            Power 66.5% – initiate Stage 2
[1] 0.6646934
sampleN.TOST(alpha=0.0294, targetpower=0.80, logscale=TRUE,
            theta1=0.8, theta2=1.25, theta0=0.95,
            CV=0.182132, design = "2x2", exact = TRUE,
            print = TRUE
                                                      Calculate total sample size:
++++++++ Equivalence test - TOST +++++++++
                                                      expected ratio 95%, CV<sub>intra</sub> 18.2%,
            Sample size estimation
                                                      80% power
Study design: 2x2 crossover
log-transformed data (multiplicative model)
alpha = 0.0294, target power = 0.8
BE margins
            = 0.8 ... 1.25
Null (true) ratio = 0.95, CV = 0.182132
```



Total sample size 20: include another 8 for Stage 2



Potvin et al. (example B/C)

```
8 subjects in Stage 2 (20 total), modified model for pooled analysis
Model Specification and User Settings
       Dependent variable : Cmax (ng/mL)
                Transform: LN
              Fixed terms : int+Sequence+Stage+Period(Stage)+Treatment
    Random/repeated terms : Sequence*Stage*Subject
Final variance parameter estimates:
Var(Sequence*Stage*Subject)
                              0.518978
            Var(Residual)
                              0.0458956
          Intrasubject CV
                              0.216714
                                                                      \alpha 0.0294 in
Bioequivalence Statistics
                                                                      pooled analysis
User-Specified Confidence Level for CI's = 94.1200
Percent of Reference to Detect for 2-1 Tests = 20.0%
A.H.Lower = 0.800 A.H.Upper = 1.250
Formulation variable: Treatment
Reference: Reference LSMean= 1.133431
                                          SE= 0.171385 GeoLSM= 3.106297
                       LSMean= 1.147870 SE= 0.171385
Test:
           Test
                                                         GeoLSM= 3.151473
    Difference =
                               Diff_SE=
                                          0.0677, df= 17.0
                      0.0144,
    Ratio(%Ref) =
                    101.4544
                                                        BE shown with 94.12% CI:
                      Classical
                                                        overall \alpha \leq 0.05!
    CI 90\% = (
                  90.1729, 114.1472)
                  88.4422, 116.3810)
   CI User = (
    Average bioequivalence shown for confidence=94.12 and percent=20.0.
```



Potvin et al. (B vs. C)

- Pros & cons
 - ■Method C (*if power* \geq 80%!) is a conventional BE study; no penality in terms of α needs to be applied
 - Method C goes to Stage 2 less often and has smaller average total sample sizes than Method B for cases where the initial sample size is reasonable for the CV
 - If the size of Stage 1 is low for the actual CV both methods go to Stage 2 almost all the time; total sizes are similar
 - Method B slightly more conservative than C





Potvin et al. (B vs. C)

- Recommendations
 - Method C preferred due to slightly higher power than method B
 - ■Plan the study as if the CV is known
 - If assumptions turn out to be true = no penalty
 - If lower power (CV_{intra} higher than expected), BE still possible in first stage (94.12% CI) or stage 2 as the safety net.
 - ■Don't jeopardize! Smaller sample sizes in the first stage than in a fixed design don't pay off. Total sample sizes are ~20% higher.





Sequential Designs

- Methods by Potvin et al. (2008) limited to point estimate of 0.95 and 80% power
 - Follow-up paper
 - Slight inflation of patient's risk (α 0.0547) observed in Methods B/C if PE 0.90 instead of 0.95 was used
 - Method D (like C, but α 0.0280 instead of α 0.0294)
 - Might be usefull if PE 0.95 and power 90% as well; not validated yet!

Montague TH, Potvin D, DiLiberti CE, Hauck WW, Parr AF, and DJ Schuirmann Additional results for 'Sequential design approaches for bioequivalence studies with crossover designs' Pharmaceut. Statist. (2011), DOI: 10.1002/pst.483





Sequential Designs

Caveats

- Methods for 'classical' group-sequential designs derived based on
 - Test for differences (superiority, parallel groups)
 - Large samples (Z test of normal distributed data with known variance)
 - Fixed total sample size (interim analysis at N/k)
 - Balanced case (no drop outs)
- Don't apply any published procedure unquestioned (i.e., if not validated for bioequivalence)
- Simulations mandatory to derive an empirical α (≤0.052)!





- Feasibility / futility rules
 - It would be desirable to stop a study after stage 1 under certain circumstances
 - (1) BE is unlikely to be shown in even very high sample sizes (e.g., CI outside acceptance range)
 - → reformulate
 - (2) It turns out that the drug/formulation is highly variable
 - → replicate design study in order to perform scaling required
 - (3) The calculated sample size exceeds the budget of the project by far





- Feasibility / futility rules
 - These points are not covered by Potvin et al.
 - If you decide to include a rule for early stopping, it's not part of the statistical procedure any more
 - (1) and (2) are ethically justifiable
 - (3) Acceptance?





- Arbitrary PE and/or power
 - Simulations mandatory
 - Set desired PE and power
 - Define maximum α -inflation (\leq 0.052?)
 - Simulate sufficiently large number of studies (N)
 - Count number of studies accepted BE at 1.25 (n₁) and number of studies rejected BE at the desired PE (n₂)
 - Empirical α = n₁/N
 - \triangleright Empirical $\beta = n_2/N$; power = 1β
 - Start with Pocock's nominal α 0.0294 and decrease stepwise if empirical α too high
 - Compiled language almost necessary (speed!)





- Adaption for stage 1 PE (full adaptive design)
 - If applied naïvely, α -inflation of up to 30%!*
 - Various methods for superiority trials, but nothing in the area of BE published
 - Simulations mandatory

* Cui L, Hung MJ, and S-J Wang

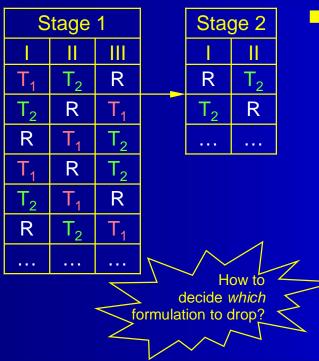
Modification of sample size in group sequential clinical trials

Biometrics 55, 853–7 (1999)





 Dropping a candidate formulation from a higher-order cross-over design



- Statistical model of BE assumes IID (common σ^2)
 - \triangleright Let's assume to continue with T_2
 - If $\sigma_{T_1} > \sigma_{T_2}$ and/or σ_R , the pooled variance in Stage 1 will be inflated. The estimated total sample size will be too high. Expensive, but no influence on α expected.
 - If $\sigma_{T_1}^2 < \sigma_{T_2}^2$ and/or σ_R^2 , power will be lower increasing the producer's risk only.



- Data of 6x3 dose proportionality study
 R 20 mg, T₁ 30 mg, T₂ 40 mg; CV_{intra} 8.76%
 - $^{\circ}$ $^{\circ}$

Stage 1							
Ī		II		III			
R	146.05	T ₂	133.26	T ₁	269.51		
T ₁	86.83	R	55.08	T ₂	52.58		
T ₂	52.78	T ₁	75.51	R	60.57		
T ₁	99.57	T ₂	57.29	R	74.45		
T ₂	80.61	R	94.62	T ₁	121.39		
R	57.10	T ₁	80.58	T ₂	52.08		
T ₁	109.79	R	59.20	T_2	55.99		
T ₂	44.07	T ₁	79.76	R	57.25		

Stage 2							
	T	П					
R	74.45	T ₂	61.72				
T ₂	54.93	R	54.71				
T ₂	43.17	R	37.49				
R	54.64	T ₂	47.32				

Extremely imbalanced due to arbitrary 'cut' of original dataset!
N=6 (single balanced block) would have zero df for sequences.





```
8 subjects in Stage 1,
Model Specification and User Settings
                                                            all effects fixed (EMA)
      Dependent variable : Response
               Transform: LN
             Fixed terms : int+sequence+treatment+period+subject(sequence)
Final variance parameter estimates:
           Var(Residual)
                           0.0068489
                                              CV<sub>intra</sub> 8.29%
Bioequivalence Statistics
User-Specified Confidence Level for CI's = 94.4000 ◀
                                                            \alpha 0.028 (Method D/B)
Percent of Reference to Detect for 2-1 Tests = 20.0%
A.H.Lower = 0.800
                    A.H.Upper = 1.250
Reference: Reference
                      LSMean= 4.332414 SE= 0.029948
                                                        GeoLSM= 76.127859
                     LSMean= 4.726674 SE= 0.029948 GeoLSM= 112.919400
          Test 1
Test:
   Difference =
                     0.3943, Diff_SE= 0.0417, df= 12.0
   Ratio(\%Ref) = 148.3286
   CI User = (135.8004, 162.0127)
   Average bioINequivalence shown for confidence=94.40 and percent=20.0.
          Test 2
                      LSMean= 4.187643 SE= 0.029948 GeoLSM= 65.867359
Test:
   Difference =
                   -0.1448.
                              Diff SE=
                                        0.0417. df= 12.0
   Ratio(%Ref) =
                   86.5220
   CI User = (79.2141, 94.5041)
   Failed to show average bioequivalence for confidence=94.40 and percent=20.0.
```



```
\alpha 0.028, expected ratio 90%,
require(PowerTOST)
power.TOST(alpha=0.0280, logscale=TRUE,
                                                    MSE 0.06849 (CV<sub>intra</sub> 8.29%),
           theta1=0.8, theta2=1.25, theta0=0.90,
                                                    8 subjects in Stage 1, 6x3 design
           CV=se2CV(sqrt(0.0068489)), n=8,
           design="3x6x3", exact=TRUE)
                            Power 76.2% <80% – initiate Stage 2
[1] 0.762231
sampleN.TOST(alpha=0.0280, targetpower=0.80, logscale=TRUE,
            theta1=0.8, theta2=1.25, theta0=0.90,
            CV=se2CV(sqrt(0.0068489)), design="3x6x3", exact=TRUE,
            print=TRUE)
                                                    Calculate total sample size:
++++++++ Equivalence test - TOST +++++++++
                                                    expected ratio 90%, CV<sub>intra</sub> 8.29%,
            Sample size estimation
                                                    80% power, keeping 6x3 design
Study design: 3x6x3 crossover
log-transformed data (multiplicative model)
alpha = 0.0294, target power = 0.8
BE margins
            = 0.8 ... 1.25
Null (true) ratio = 0.9, CV = 0.0829
Sample size
                      Total sample size 12: include another 4 for Stage 2
       power
12
     0.920990
```





Model Specification and User Settings Dependent variable : Response Transform: LN Fixed terms : int+Sequence+Stage+Period(Stage)+Treatment Random/repeated terms : Sequence*Stage*Subject Final variance parameter estimates:

Var(Residual) 0.00667999

4 subjects in Stage 2 (12 total), modified model for pooled analysis

```
Bioequivalence Statistics
User-Specified Confidence Level for CI's = 94.4000
Percent of Reference to Detect for 2-1 Tests = 20.0%
A.H.Lower = 0.800
                   A.H.Upper = 1.250
Reference: Reference LSMean= 4.045115 SE= 0.103862 GeoLSM= 57.117740
                    LSMean= 4.455914 SE= 0.106556 GeoLSM= 86.134878
          Test 1
Test:
   Difference =
                    0.4108, Diff_SE= 0.0394, df= 14.985
   Ratio(\%Ref) = 150.8023
   CI User = (138.9762, 163.6348)
   Average bioINequivalence shown for confidence=94.40 and percent=20.0.
          Test 2
                     LSMean= 3.933423 SE= 0.103862 GeoLSM= 51.081521
Test:
                   -0.1117, Diff_SE= 0.0335, df= 14.985
   Difference =
   Ratio(%Ref) =
                   89.4320
   CI User = (83.4279, 95.8682)
   Average bioequivalence shown for confidence=94.40 and percent=20.0.
```





- Lessons learned, open questions
 - Not validated! Don't think about using it at all!
 - Note that due to the massive imbalance the LSM of Test 1 (although not included in Stage 2) changed from Stage 1 in the pooled analysis!

■Stage 1: 112.92

Pooled: 86.13

Drug has low CV_{intra}, but high CV_{inter} – Apples and oranges?

CV%	T ₁	T ₂	R	model
Stage 1	26.86	34.15	37.32	period
Stage 2	_	18.08	24.79	period
Pooled	26.86	32.01	35.92	period



- Lessons learned, open questions
 - Must use software in the power calculation which can handle the degrees of freedom of a Williams' design in Stage 1 correctly (e.g., PowerTOST)
 - Obvious which formulation to drop in this example, but what if formulations are similar in PEs? Keep the one with smaller CV_{inter}?
 - Design in the sample size estimation of Stage 2?
 - \blacksquare 3×6 (block size 6 → 12)
 - \blacksquare 2×2 (block size 2 → 10)
 - The latter would have failed in the example





- Lessons learned, open questions
 - Tempting idea, but not recommended
 - until a statistical decision tree is developed and
 - suitable simulations have shown that the patient's risk is not inflated





- Replicated designs (HVDs/HVDPs)
 - Nothing published!
 - Statistical model?
 - Although EMA assumes equal variances of formulations (Q&A document Jan 2010) that does not reflect the 'real world' (quite often $\sigma^2_{WR} > \sigma^2_{WT}$)
 - If you set up simulations allow for different variances of test and reference



Congratulations! Power and intra-subject variability in 2 stage approaches to BE approval Open Questions?



Helmut Schütz BEBAC

Consultancy Services for Bioequivalence and Bioavailability Studies 1070 Vienna, Austria helmut.schuetz@bebac.at





To bear in Remembrance...

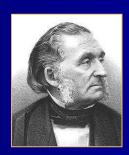
Power. That which statisticians are always calculating but never have.

Power: That which is wielded by the priesthood of clinical trials, the statisticians, and a stick which they use to beta their colleagues.



Power Calculation – A guess masquerading as mathematics.

Stephen Senn



You should treat as many patients as possible with the new drugs while they still have the power to heal.

Armand Trousseau