

# Adaptive clinical trials with subgroup selection

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# Setting

Definitive comparison of experimental treatment with control

Single predefined subgroup of interest

Research questions: is treatment effective in whole population

test  $H_0^{\{F\}}$

is treatment effective in subgroup

test  $H_0^{\{S\}}$

Confirmatory study:

wish to control risk of any false positive result

(Wang et al 2007, Song & Chi 2007, Brannath et al 2009,  
Spiessens & Debois 2010, Jenkins et al 2011)

## Adaptive design – idea

We are testing hypotheses in full population and subgroup

If we knew we could focus on subgroup, could recruit only subgroup patients

Need to adjust for multiple hypotheses to control error rate  
This makes it harder to show efficacy

If we knew which hypothesis to test, could focus on that

Adaptive design:

- conduct interim analysis partway through trial
- use interim data to guide recruitment and hypothesis testing in remainder of trial

# Adaptive design – details

Two-stage trial

Stage 1: Recruit  $n_1$  patients per group from full population

On basis of interim data decide to continue to

- (i) test  $H_0^{\{F\}}$  and  $H_0^{\{S\}}$  at final analysis
- (ii) test  $H_0^{\{F\}}$  only final analysis
- (iii) test  $H_0^{\{S\}}$  only final analysis

(possibly use interim data on short-term endpoint  
or external information)

# Adaptive design – details

Stage 2: Recruit further  $n_2$  patients per group

If testing  $H_0^{\{F\}}$  and  $H_0^{\{S\}}$  or  $H_0^{\{F\}}$  alone:

continue to recruit from full population

If testing  $H_0^{\{S\}}$  alone: recruit from subgroup only  
(possibly with enrichment)

Final analysis:

Test selected hypothesis/hypotheses

Control familywise error rate allowing  
for hypothesis selection

(Song & Chi 2007, Brannath et al 2009, Jenkins et al 2011)

# Hypothesis testing

Test  $H_0^{\{F\}}$  (full population) and  $H_0^{\{S\}}$  (sub population)

Require strong control of family wise error rate (FWER):

$$Pr(\text{erroneously reject either } H_0^{\{F\}} \text{ or } H_0^{\{S\}}) = \alpha$$

under  $H_0^{\{F\}}$  or  $H_0^{\{S\}}$  or  $H_0^{\{F\}} \cap H_0^{\{S\}}$

# Adaptive design – ‘ingredients’

We need:

hypothesis testing approach to strongly control  
FWER allowing for multiple hypotheses

method for combination of evidence from two stages

decision rule for deciding which  
hypothesis/hypotheses to consider in stage 2

# Test statistics

Test  $H_0^{\{F\}}$  (full population) and  $H_0^{\{S\}}$  (sub population)

At stage  $i$ , let

$p_i^{\{F\}}$  be p-value for testing  $H_0^{\{F\}}$  (full population)

$p_i^{\{S\}}$  be p-value for testing  $H_0^{\{S\}}$  (sub population)

$Z_i^{\{F\}}$  be test statistic for testing  $H_0^{\{F\}}$  (full population)

$$Z_i^{\{F\}} = \Phi^{-1}(1 - p_i^{\{F\}})$$

$Z_i^{\{S\}}$  be test statistic for testing  $H_0^{\{S\}}$  (sub population)

$$Z_i^{\{S\}} = \Phi^{-1}(1 - p_i^{\{S\}})$$



## Closed testing procedure

Extend family of hypotheses to include

$$H_0^{\{F\}}, H_0^{\{S\}}, H_0^{\{F,S\}} = H_0^{\{F\}} \cap H_0^{\{S\}}$$

Perform 'local' level  $\alpha$  test of each hypothesis

Reject  $H_0^{\{F\}}$

if and only if  $H_0^{\{F\}}$  and  $H_0^{\{F\}} \cap H_0^{\{S\}}$  are locally rejected

Reject  $H_0^{\{S\}}$

if and only if  $H_0^{\{S\}}$  and  $H_0^{\{F\}} \cap H_0^{\{S\}}$  are locally rejected

Controls FWER in strong sense

Requires level test of intersection hypothesis  $H_0^{\{F,S\}}$

# Tests of the intersection hypothesis

At stage  $i$ , base test of  $H_0^{\{F,S\}}$  on p-value  $p_i^{\{F,S\}}$

## Bonferroni test

$$p_i^{\{F,S\}} = 2 \min\{p_i^{\{F\}}, p_i^{\{S\}}\}$$

## Simes test

$$p_i^{\{F,S\}} = \min\{2 \min\{p_i^{\{F\}}, p_i^{\{S\}}\}, \max\{p_i^{\{F\}}, p_i^{\{S\}}\}\}$$

(Simes 1986)

These tests ignore correlation between  $p^{\{F\}}$  and  $p^{\{S\}}$

# Tests of the intersection hypothesis

## Spiessens and Debois test

Under  $H_0^{\{S\}} \cap H_0^{\{F\}}$

$$\begin{pmatrix} Z_i^{\{F\}} \\ Z_i^{\{S\}} \end{pmatrix} \sim N \left( \begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \sqrt{\tau} \\ \sqrt{\tau} & 1 \end{pmatrix} \right)$$

where  $\tau$  is proportion in subgroup

Obtain  $p_i^{\{F,S\}}$  based on distribution of  $\max\{Z_i^{\{S\}}, Z_i^{\{F\}}\}$

(Spiessens and Debois 2010)

# Combining stages 1 and 2

## Combination test

Obtain overall p-value for each hypothesis using pre-specified combination function

E.g. inverse normal combination test for based on

$$w_1\Phi^{-1}(1 - p_1^{\{F\}}) + w_2\Phi^{-1}(1 - p_2^{\{F\}})$$

for pre-specified  $w_1$  and  $w_2$  with  $w_1^2 + w_2^2 = 1$

Requirement is that p-values are independent  
(or at least the p-clud condition holds)

(Brannath et al 2002)

# Combining stages 1 and 2

## Conditional error function approach

Obtain design assuming testing both hypotheses

At interim analysis obtain error rate for second stage  
conditional on stage 1 data

Can redesign stage 2 so long as conditional  
error rate is controlled

e.g. restrict testing to full population or subgroup alone

(Müller and Schäfer 2001, Friede et al 2011)

## Decision rule

Base hypothesis selection on estimated treatment effects:

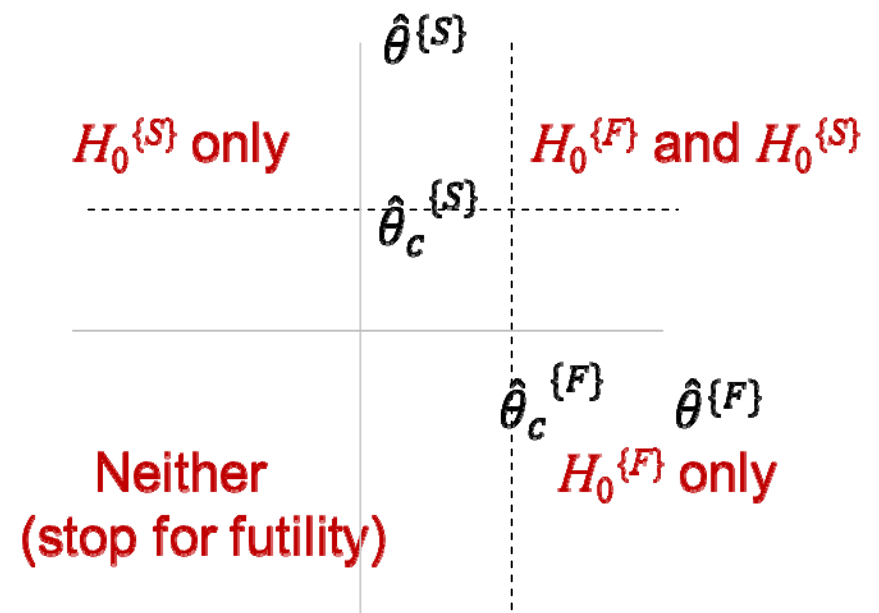
$\hat{\theta}^{\{F\}}$  (full population),  $\hat{\theta}^{\{S\}}$  (sub population)

Test  $H_0^{\{F\}}$  if and only if

$$\hat{\theta}^{\{F\}} \geq \hat{\theta}_c^{\{F\}}$$

Test  $H_0^{\{S\}}$  if and only if

$$\hat{\theta}^{\{S\}} \geq \hat{\theta}_c^{\{S\}}$$



(Jenkins et al 2011)

## Decision rule

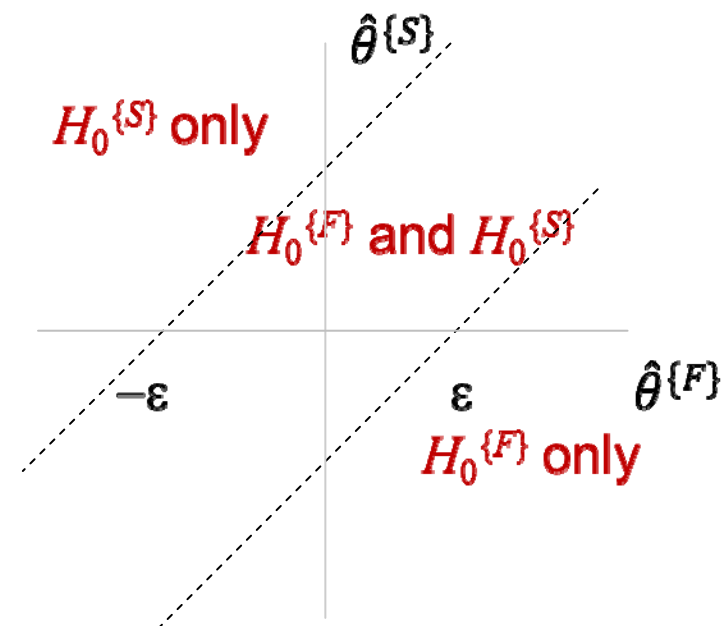
Base hypothesis selection on estimated treatment effects:

$\hat{\theta}^{\{F\}}$  (full population),  $\hat{\theta}^{\{S\}}$  (sub population)

Test  $H_0^{\{F\}}$  or  $H_0^{\{S\}}$  according to maximum of  $\hat{\theta}^{\{F\}}$  and  $\hat{\theta}^{\{S\}}$

Test both if

$$|\hat{\theta}^{\{F\}} - \hat{\theta}^{\{S\}}| \leq \varepsilon$$



(Friede et al 2011)

# Simulation study

## Model:

Normally distributed test statistics  
Standardised treatment difference:  
0.3 in subgroup  
0 outside subgroup

**Subgroup prevalence: 1% to 50%**



# Simulation study

## Designs:

Adaptive designs: CEF test with Spiessens and Debois test  
combination test with Spiessens test  
combination test with Simes test

Fixed designs: single study testing both hypotheses  
two separate studies: second to test  
hypothesis selected by first

## Sample size:

$$n_1 = 200, n_2 = 200$$

fixed single stage:  $n = 400$

if enrichment:

all  $n_2$  from subgroup if test  $H_0^{\{S\}}$  only

# Simulation study results

## Without enrichment

Adaptive:

CEF

Comb test Simes

Comb test Spiessens

Fixed:

Separate studies

Single study

power

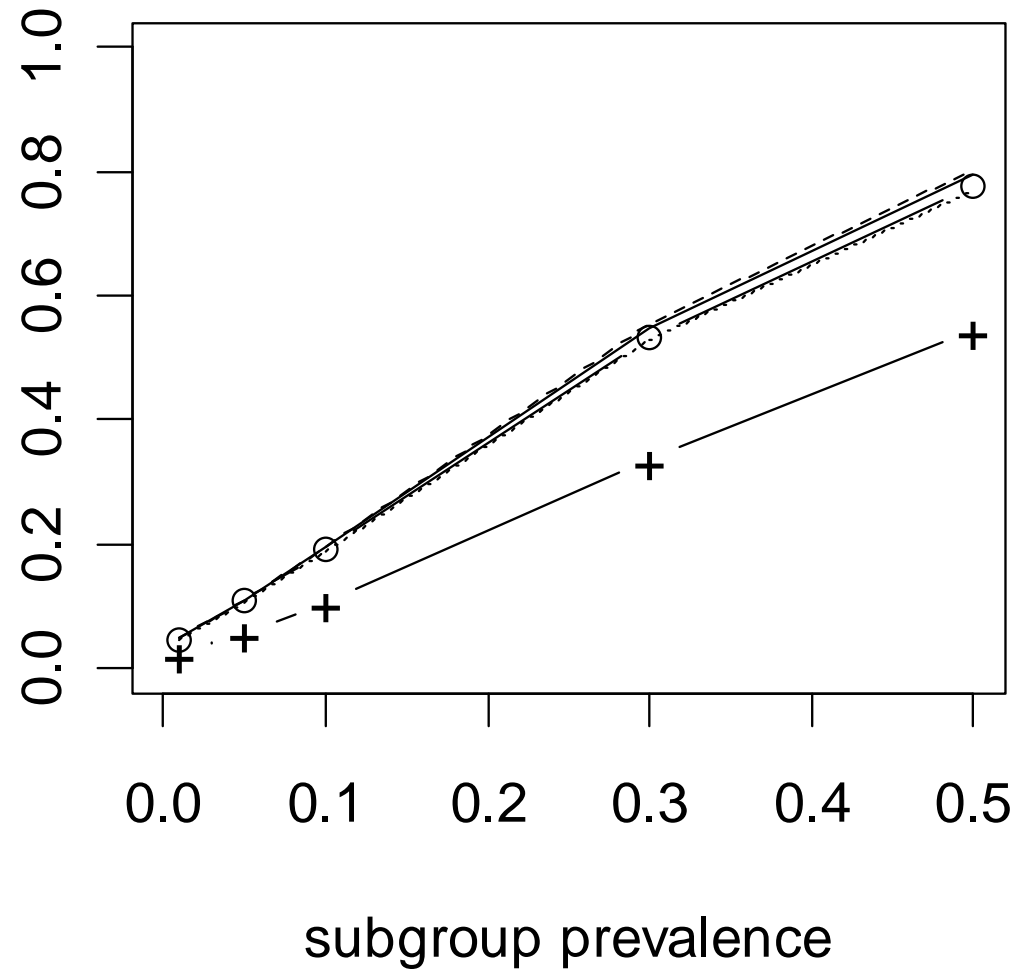
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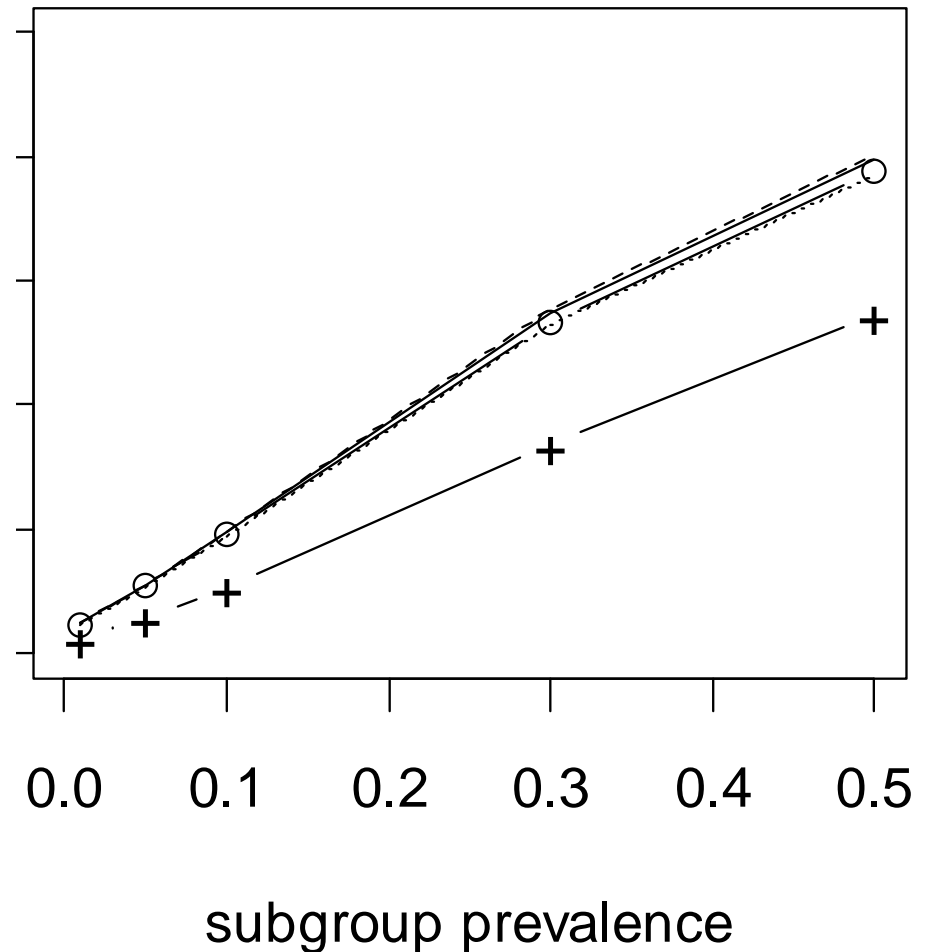


# Simulation study results

## Without enrichment

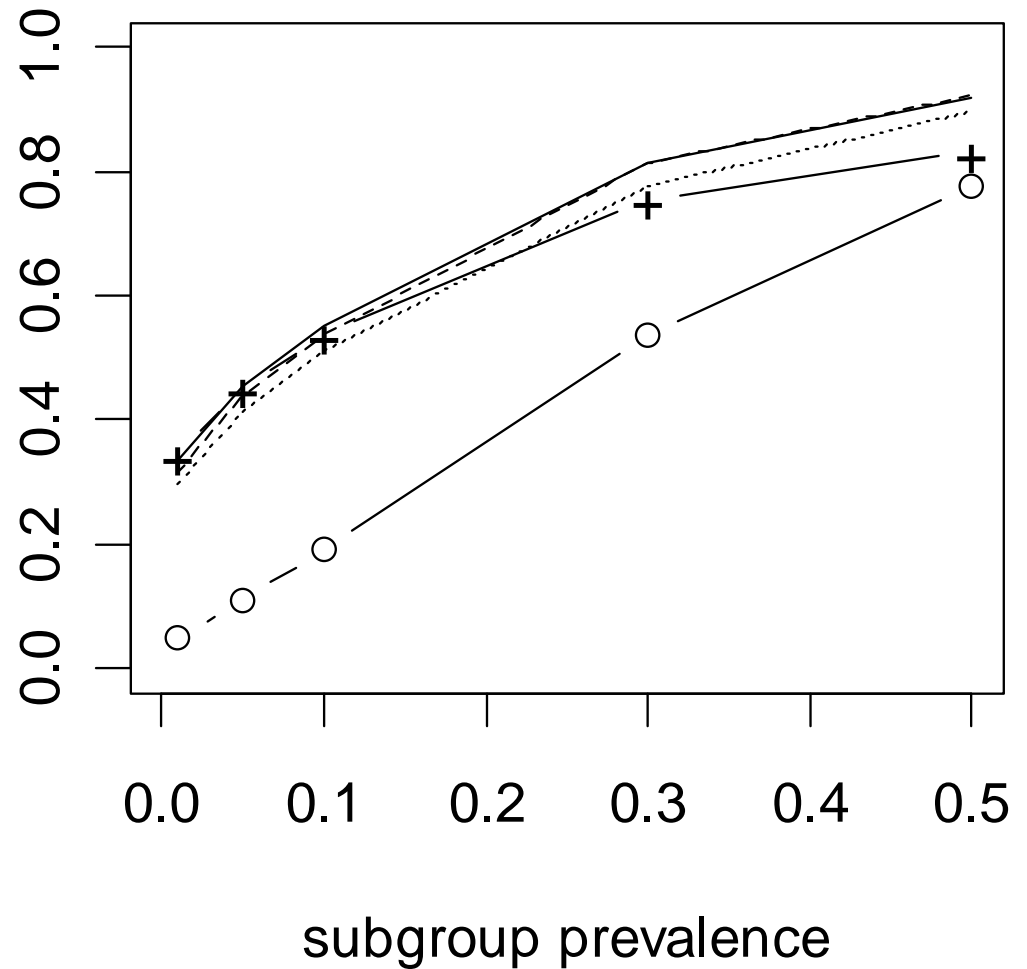
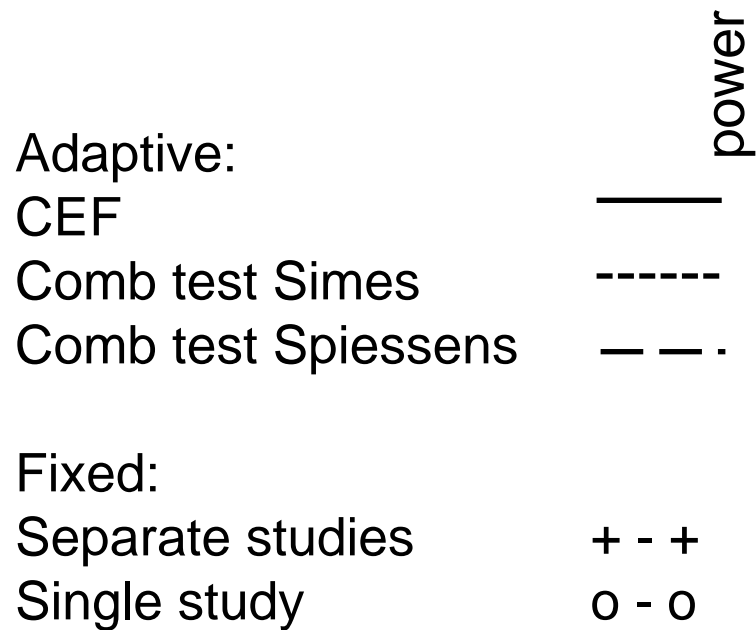
Key messages:

- Power increases with subgroup size
- Including data from both stages increases power
- Gain from allowing testing of only one hypothesis in second stage is relatively small
- Adaptive designs are very similar (Simes method slightly less powerful)



# Simulation study results

With enrichment

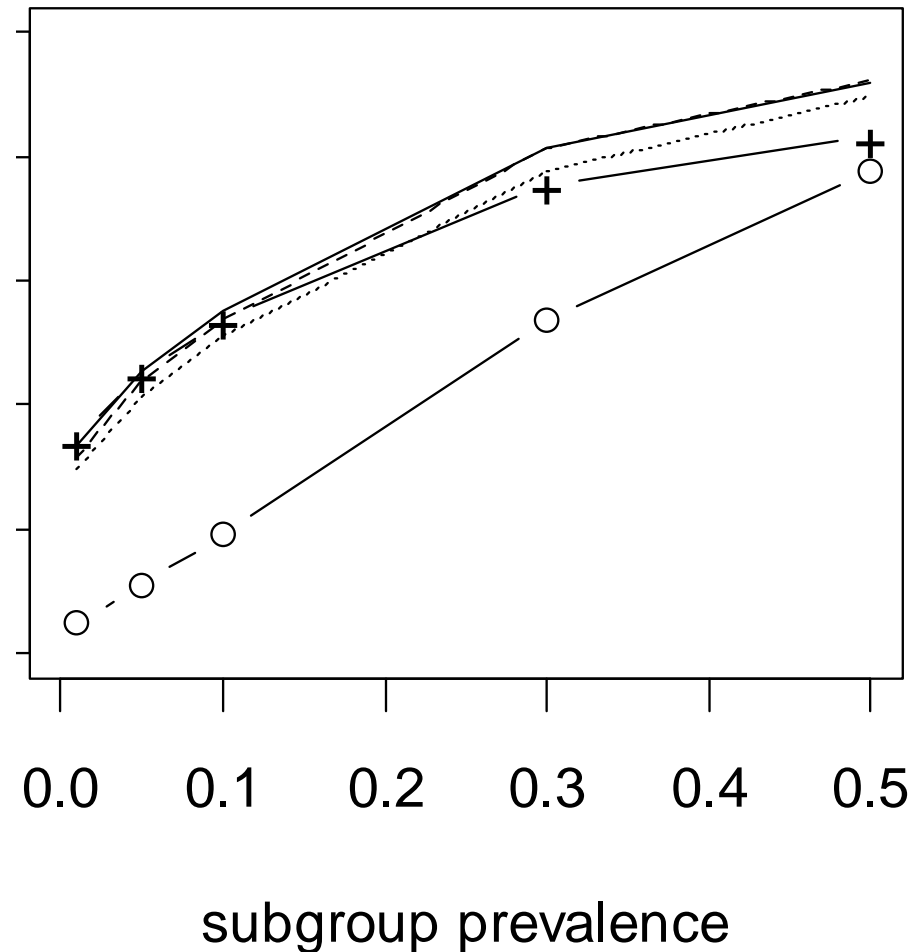


# Simulation study results

## With enrichment

Key messages:

- Enrichment increases power, reduces effect of subgp. size
- Single stage design (without enrichment) is less powerful
- Gain from including first stage data is relatively small, particularly for small subgroup
- Adaptive designs are similar (Simes method slightly less powerful)



# Conclusions

We may want to test treatment in a subgroup in addition to full population

In confirmatory test need to control overall error rate

Adaptive design allows use of interim analysis to

(i) select subgroup and enable enrichment

(ii) select hypothesis(hypotheses) for final analysis

A number of methods exists to control overall error rate

# Conclusions

When possible, enrichment increases power considerably

Adaptive design can increase power by using data from both stages

Adaptive methods that allow for correlation between full- and subgroup tests are slightly more powerful

We have assumed a pre-defined subgroup. Allowing for use of interim data to select subgroup is harder!

# References

- Brannath et al. Confirmatory adaptive designs with Bayesian decision tools for a targeted therapy in oncology. *Stat Med* 2009; 28: 1445–1463.
- Brannath, Posch, Bauer. Recursive combination tests. *J. Am. Stat. Ass.* 2002, 97, 236-44.
- Jenkins, Stone, Jennison. An adaptive seamless phase II/III design for oncology trials with subpopulation selection using correlated survival endpoints. *Pharm Stat* 2011; 10: 347–56.
- Friede, Parsons, Stallard. A conditional error function approach for subgroup selection in adaptive clinical trials. *Stat Med*. In press.
- Müller, Schäfer. Adaptive group sequential designs for clinical trials: Combining the advantage of adaptive and of classical group sequential approaches. *Biometrics* 2001; 57: 886–91.
- Simes. An improved Bonferroni procedure for multiple test of significance. *Biometrika* 1986; 73: 751–4.
- Song, Chi. A method for testing a prespecified subgroup in clinical trials. *Stat Med* 2007; 26: 3535-49.
- Spiessens, Debois. Adjusted significance levels for subgroup analysis in clinical trials. *Cont Clin Trials* 2010; 31: 647–56.
- Wang, O’Neill, Hung. Approaches to evaluation of treatment effect in randomised clinical trials with genomic subset. *Pharm Stat* 2007; 6: 227–4.