

# A FRAMEWORK FOR SIMULATIONS IN CLINICAL RESEARCH

**with applications in small populations and rare diseases**

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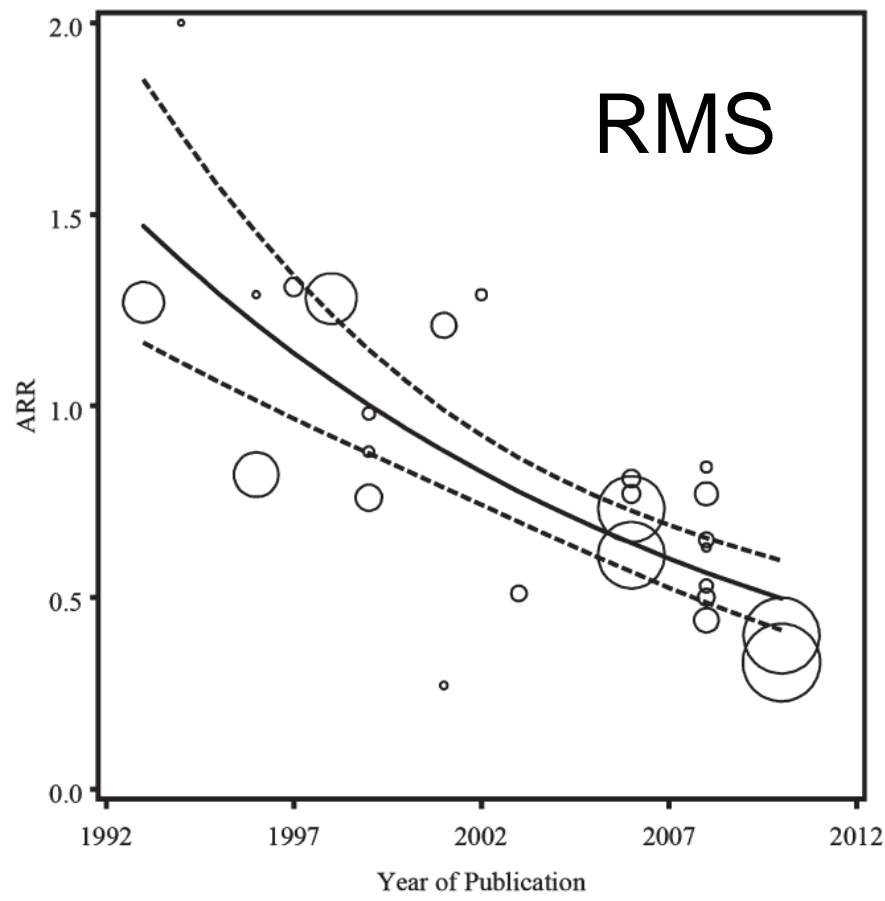
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## ACKNOWLEDGEMENTS

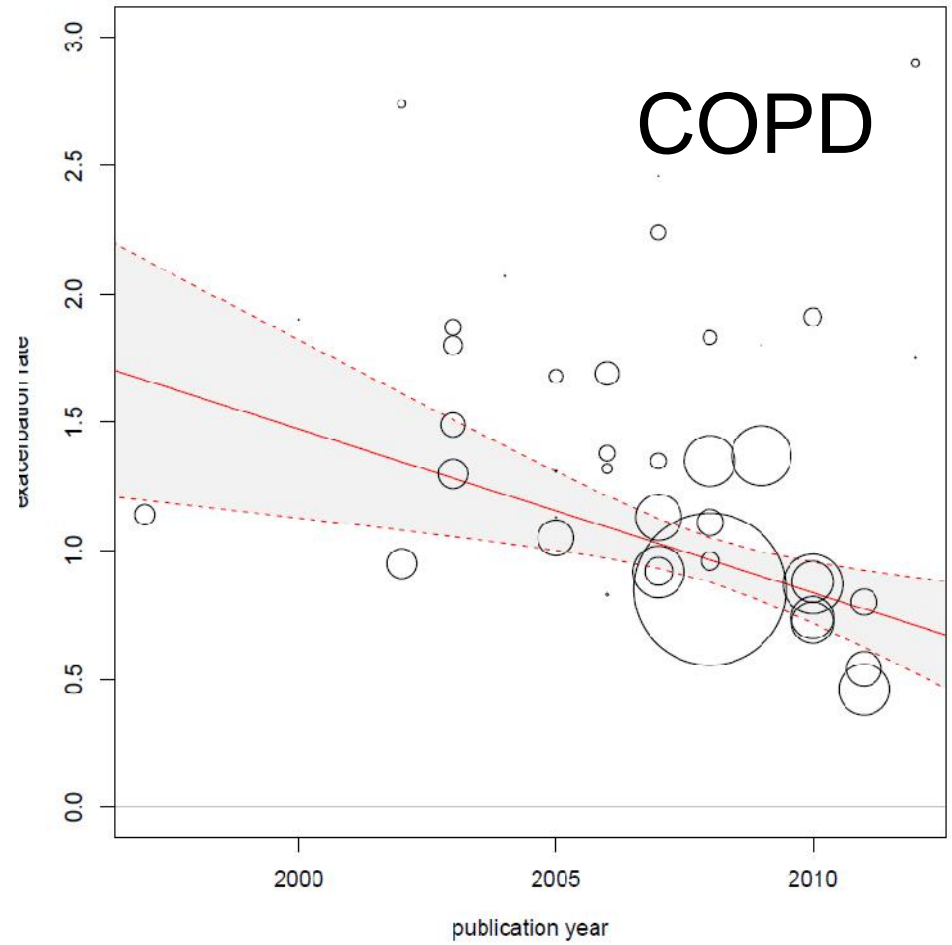


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- ▶ The worked **examples** are joint work with
  - ▶ Frank Konietschke (Dallas), Markus Pauly (Ulm)
  - ▶ Christian Röver (Göttingen)

# Trends in Placebo Event rates in Chronic Conditions

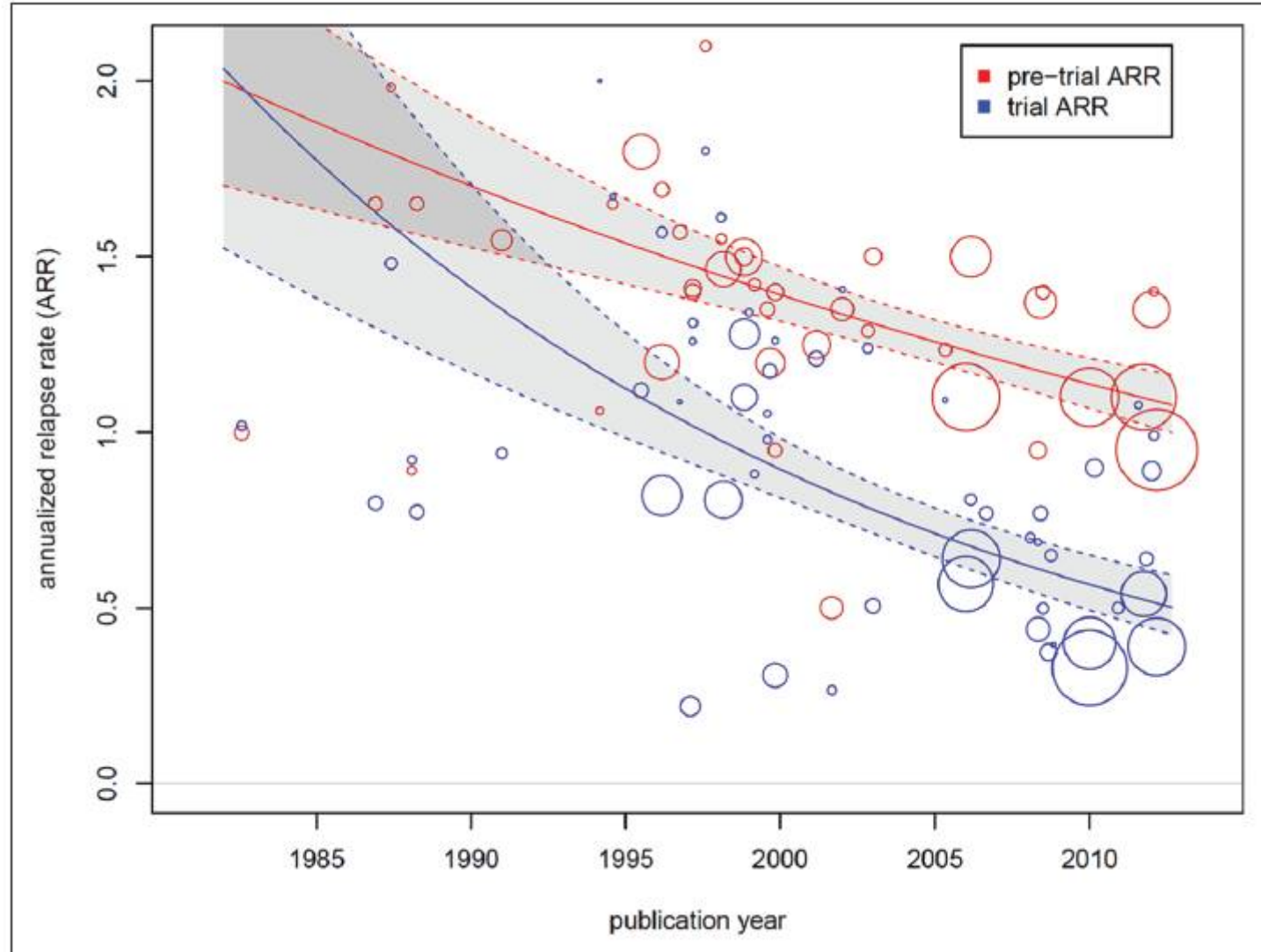


Nicholas et al. (2011) MSJ



Andreas et al. (2017)

# SHIFTING PATIENT POPULATIONS: Example in relapsing multiple sclerosis



Steinvorth et al. (2013) MSJ

## BACKGROUND

- ▶ With rising **pressure on resources** for clinical trials and **shifting patient populations** there is an increasing **demand for efficient and robust clinical trials**.
- ▶ As a consequence the way clinical trials are planned, conducted and analysed is changing with a move to **more complex designs and analysis methods**, which in turn leads to more frequent use of **Monte Carlo simulations** to plan individual clinical trials or entire clinical development programmes consisting of multiple clinical trials.

# CLINICAL SCENARIO EVALUATION (CSE)

## ▷ **Purpose of the CSE framework**

- ▷ Support structured and early planning
- ▷ Exploration of efficient approaches
- ▷ Assessment of robustness (e.g. reliance on assumptions)

## ▷ **Framework for the assessment of competing strategies**

- ▷ Analysis level
- ▷ Clinical trial level
- ▷ Series / programme of clinical trials

# COMPONENTS OF THE CSE FRAMEWORK

- ▷ **Assumption set** (underlying „truth“)
  - ▷ effect size, variability/correlation, distributions
  - ▷ structural models, dose-response shapes, etc.
  - ▷ missing value and dropout patterns
- ▷ **Set of options**
  - ▷ different designs, analysis strategies, endpoints, etc
- ▷ **Metrics:** Evaluation criteria / operational characteristics
  - ▷ efficiency: success probability, time, cost
  - ▷ validity: type 1 error rate, bias, etc.

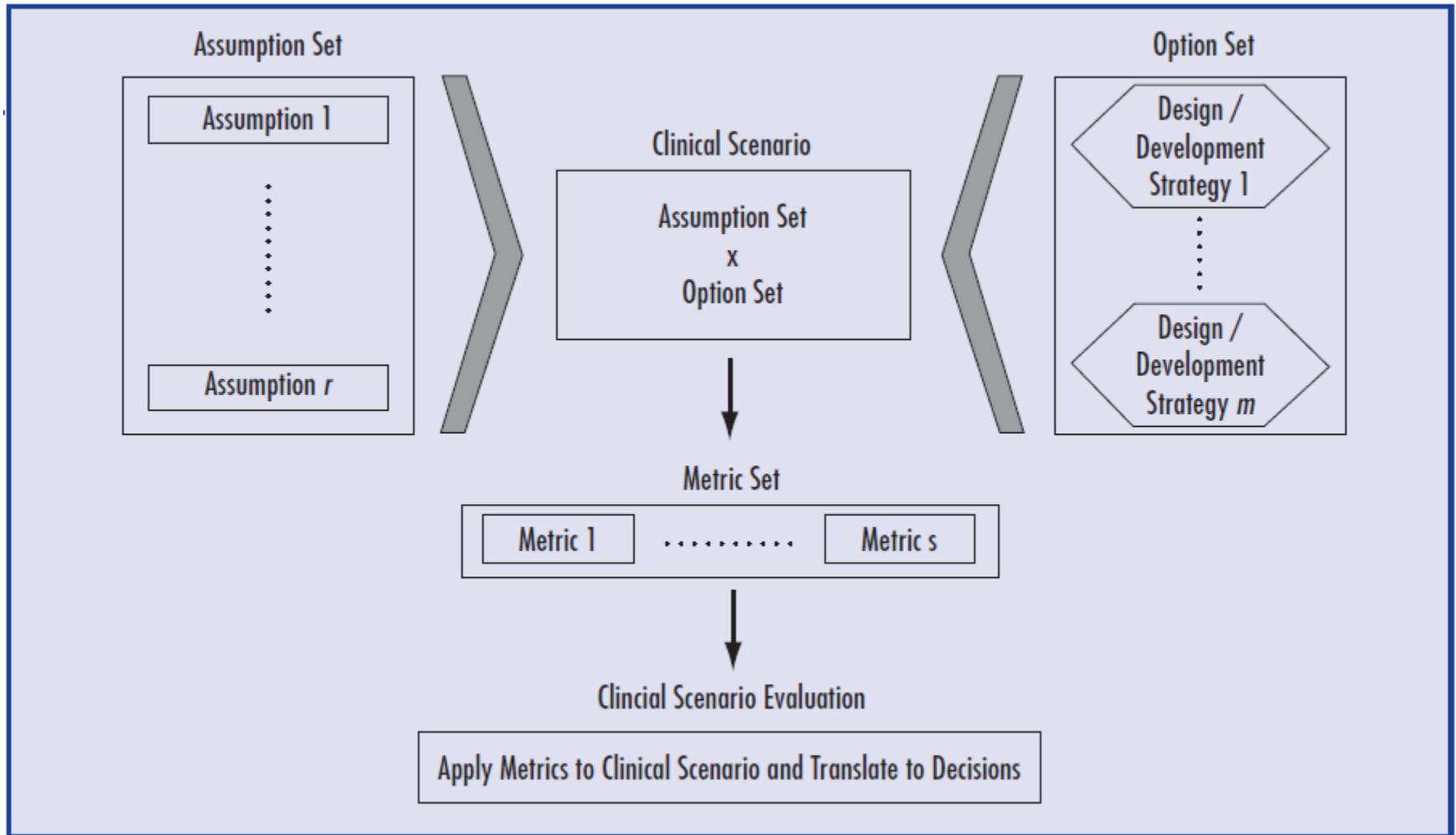


Figure 2 from Benda et al (2010) DIJ



# REFINED CSE FRAMEWORK

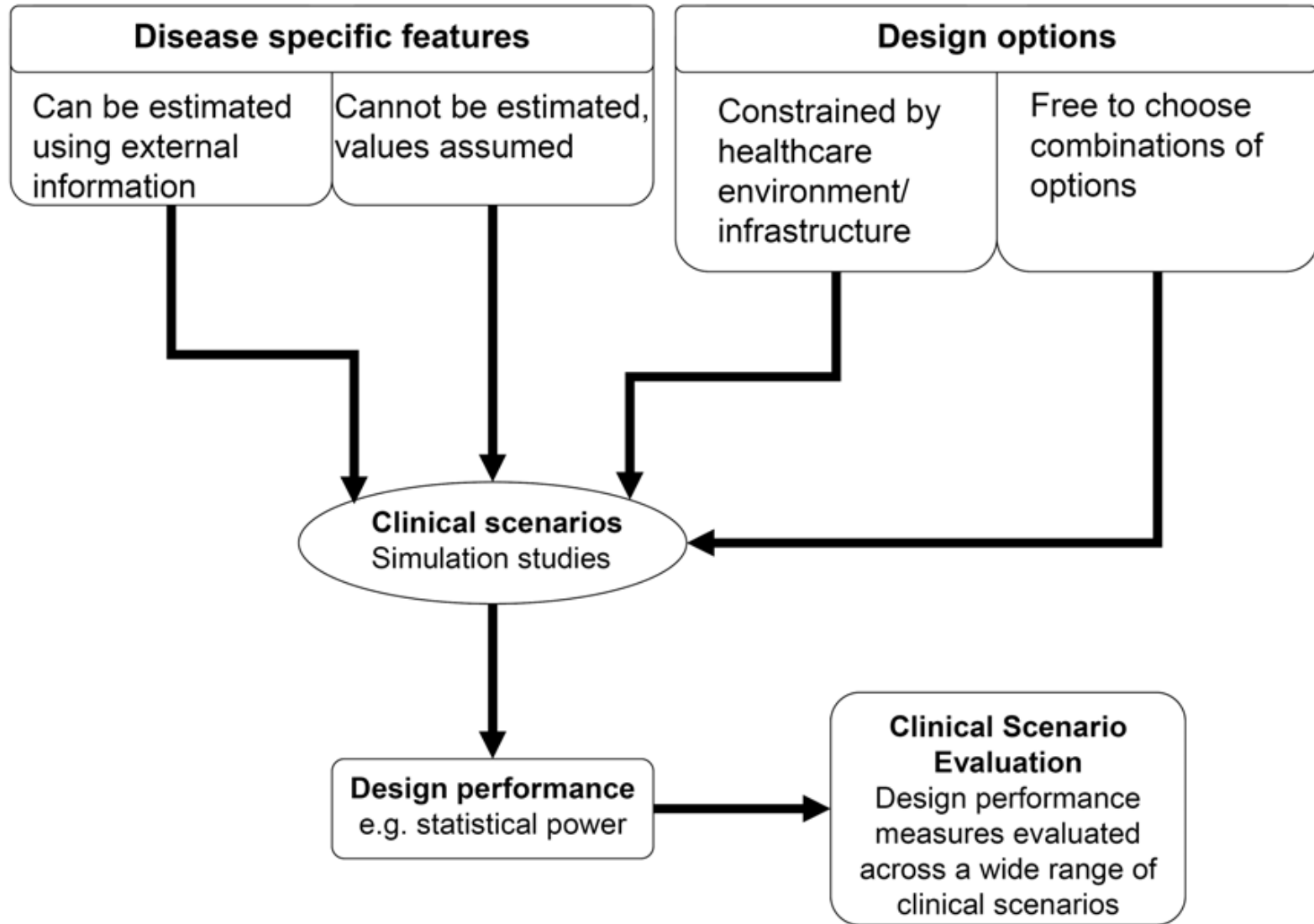


Figure 1 from Friede et al (2010) DIJ

## EXAMPLE: MRI LESIONS IN RELAPSING MS

- ▶ **MRI lesion counts:** typical phase II endpoints in relapsing MS
- ▶ Total number of gadolinium enhancing lesions in monthly MRI scans over six months reported by Kappos et al. (2006)

**Table 2. MRI and Clinical End Points at 6 Months in the Core Study.**

End Point	Placebo	Fingolimod, 1.25 mg	Fingolimod, 5.0 mg	P Value	
				1.25 mg vs. Placebo	5.0 mg vs. Placebo
<b>Primary MRI analysis population</b>					
No. evaluated	81	83	77		
Total cumulative no. of gadolinium-enhanced lesions					
Mean ±SD	14.8±22.5	8.4±23.7	5.7±11.6	<0.001	0.006
Median (range)	5 (0–114)	1 (0–182)	3 (0–91)		

- ▶ **Overdispersion:** variance 24 - 67 times larger than mean
- ▶ **Negative binomial distribution** suggested to model MRI lesion counts (e.g. Sormani et al., 1999)

## SMALL SAMPLES AND RARE DISEASES

- ▶ RCT in **paediatric multiple sclerosis** (Pakdamen et al, 2006)
  - ▶ assessing efficacy and safety of interferon beta-1a compared to no treatment
  - ▶ N=16 patients randomized
  - ▶ Endpoints: relapse rates and new T2 lesions
- ▶ Phase II trial of autologous mesenchymal **stem cells** in MS
  - ▶ relapsing-remitting MS patients not responding to at least a year of approved therapy
  - ▶ efficacy endpoint: cumulative number of gadolinium-enhancing lesions (GEL)
  - ▶ N=9 patients randomized (planned n=16)

# EXAMPLE: CSE TO INFORM CHOICE OF ANALYSIS METHOD

## ▷ **Assumptions**

- ▷ Distribution (e.g. NB), group-specific / common overdispersion parameter, size of treatment effect etc.

## ▷ **Options**

- ▷ Analysis method: Test statistic and reference distribution

## ▷ **Metrics**

- ▷ Type I error rate
- ▷ Power / sample size

## STATISTICAL MODEL AND HYPOTHESES

- ▶ **Statistical model:**  $X_{ik} \sim NB(t_{ik}\lambda_i, \phi_i)$ ,  $i = 1, 2; k = 1, \dots, n_i$ 
  - ▶ allowing for varying follow-up times, group-specific overdispersion parameters
  
- ▶ **Hypotheses:**  $H_0 : h(\lambda_1, \lambda_2) = \theta$  versus  $H_1 : h(\lambda_1, \lambda_2) \neq \theta$ ,  $\theta \in \mathbb{R}$

e.g.  $h(\lambda_1, \lambda_2) = \lambda_1 - \lambda_2$  or  $h(\lambda_1, \lambda_2) = \lambda_1/\lambda_2$ .

# WALD-TYPE STATISTICS

## ▷ Wald-type test statistics

$$T_{(h)}^{\pi(c)} = f^{(c)} \frac{\left( h \left( \widehat{\lambda}_1^{\pi(c)}, \widehat{\lambda}_2^{\pi(c)} \right) - \theta \right)}{\widehat{\sigma}_{(c)}^{\pi}}$$

## ▷ Variance estimators

- ▷ Moment estimator (simpler to compute; unbiased; more robust to model misspecifications)
- ▷ Maximum-likelihood estimator (smaller variance under assumed model)

# REFERENCE DISTRIBUTION

## ▷ Normal approximation

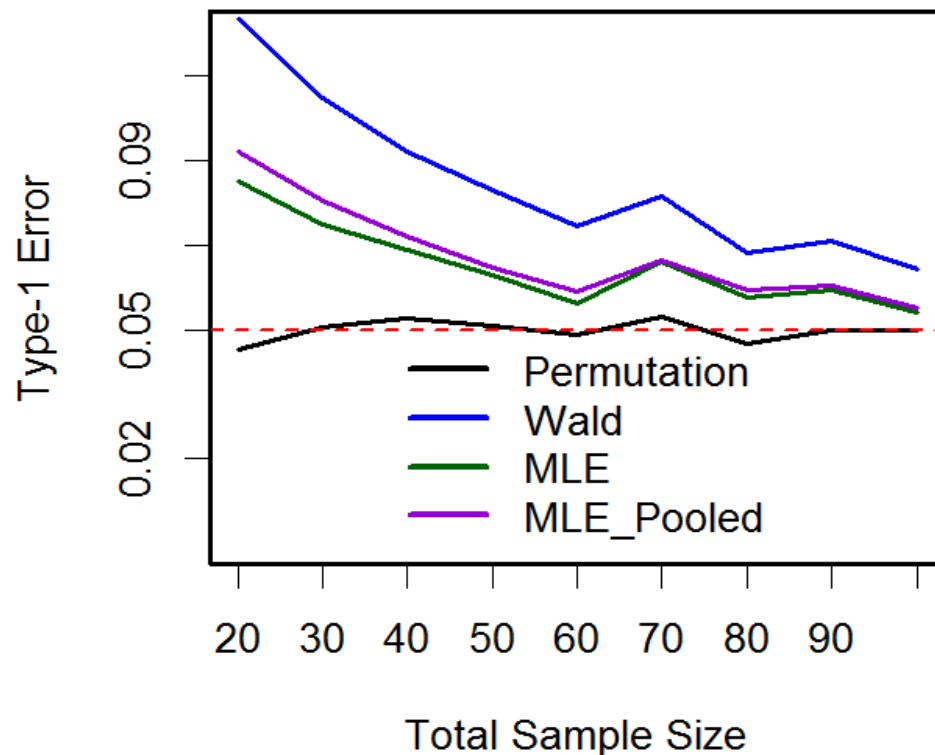
- ▷ Use  $(1 - \alpha/2)$  – quantile ( $z_{1-\alpha/2}$ ) of standard normal distribution as critical value

## ▷ Resampling

- ▷ Permutations to estimate quantile
- ▷ Due to overdispersion and varying follow-up times data are not exchangeable even under the null hypothesis
- ▷ Idea: compute Wald-type statistic for each permutation and repeat procedure several times (e.g. 10,000 times)

# TYPE I ERROR RATE

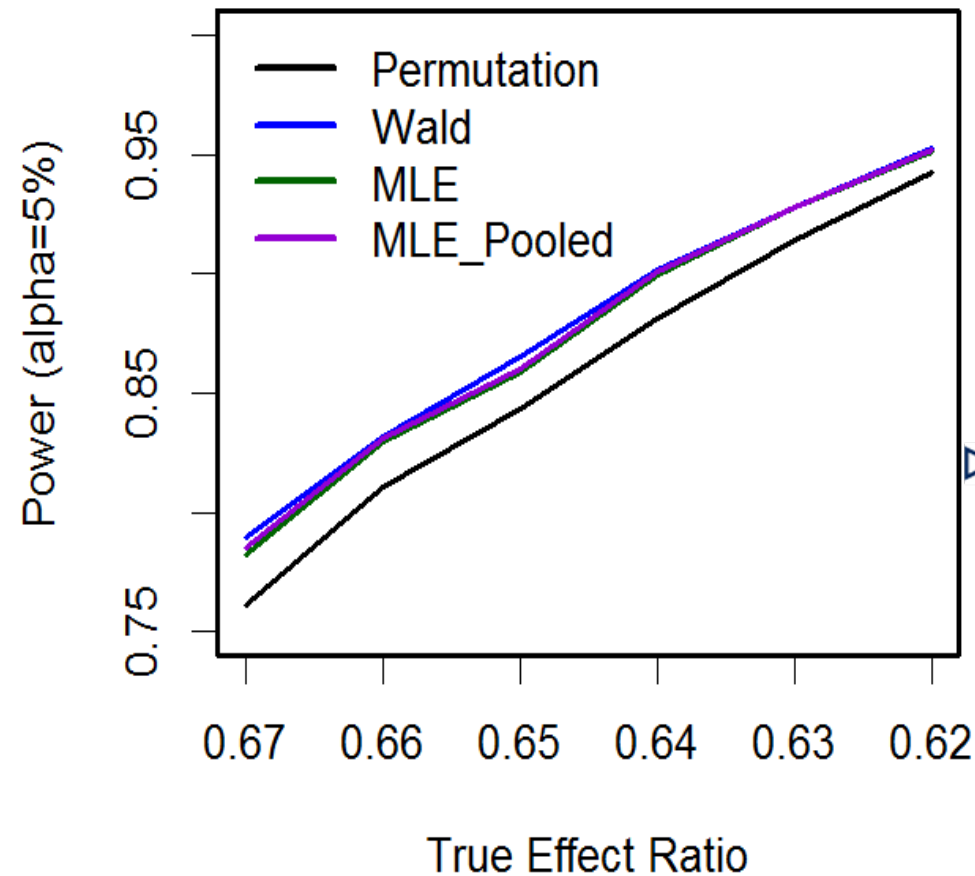
Effect: Ratio  
Allocation Ratio: 1:1



- ▷ **Simulation study motivated by MRI lesion counts in MS**
  - ▷ Mean 10.0
  - ▷ Overdispersion parameter  $\varphi_1 = \varphi_2 = 2.9$
  - ▷ Variance / mean =  $1 + 10 \times 2.9 = 30$
  - ▷ **Permutation test controls rate at nominal level**



# POWER



▷ **Simulation study** motivated by MRI lesion counts in MS

▷ Sample size: 100 patients per group

▷ Type I error rate close to nominal level in this situation

▷ **Power of permutation test**

▷ 1 -2 percentage points lower: Price to pay for robustness

▷ Compensated by increase in sample sizes of about 5%

$$\frac{(z_{0.975} + z_{0.85})^2}{(z_{0.975} + z_{0.83})^2} \approx 1.05$$

# EXAMPLES FOR EXTRAPOLATION IN RARE DISEASES AND SMALL POPULATIONS

- ▶ A small RCT and observational data
- ▶ Extrapolation from adults to children

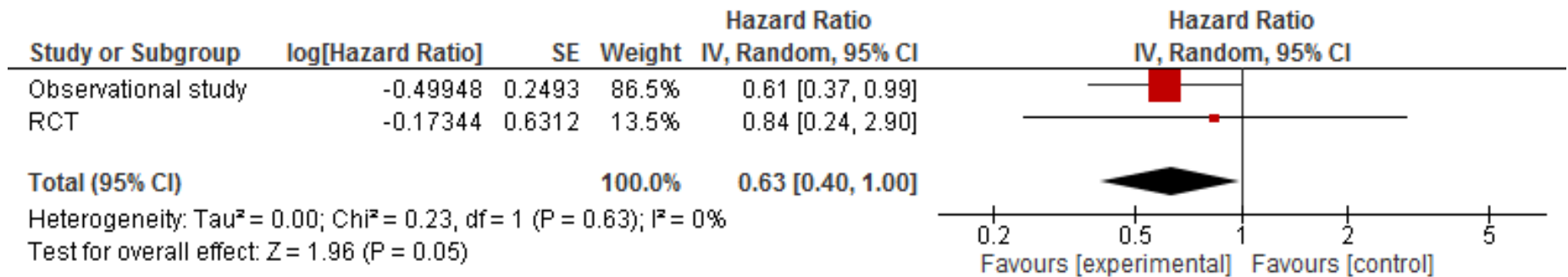
# EXAMPLE: DOXYCYCLINE IN EARLY CREUTZFELDT-JAKOB DISEASE (CJD)

## ▶ Creutzfeldt-Jakob disease

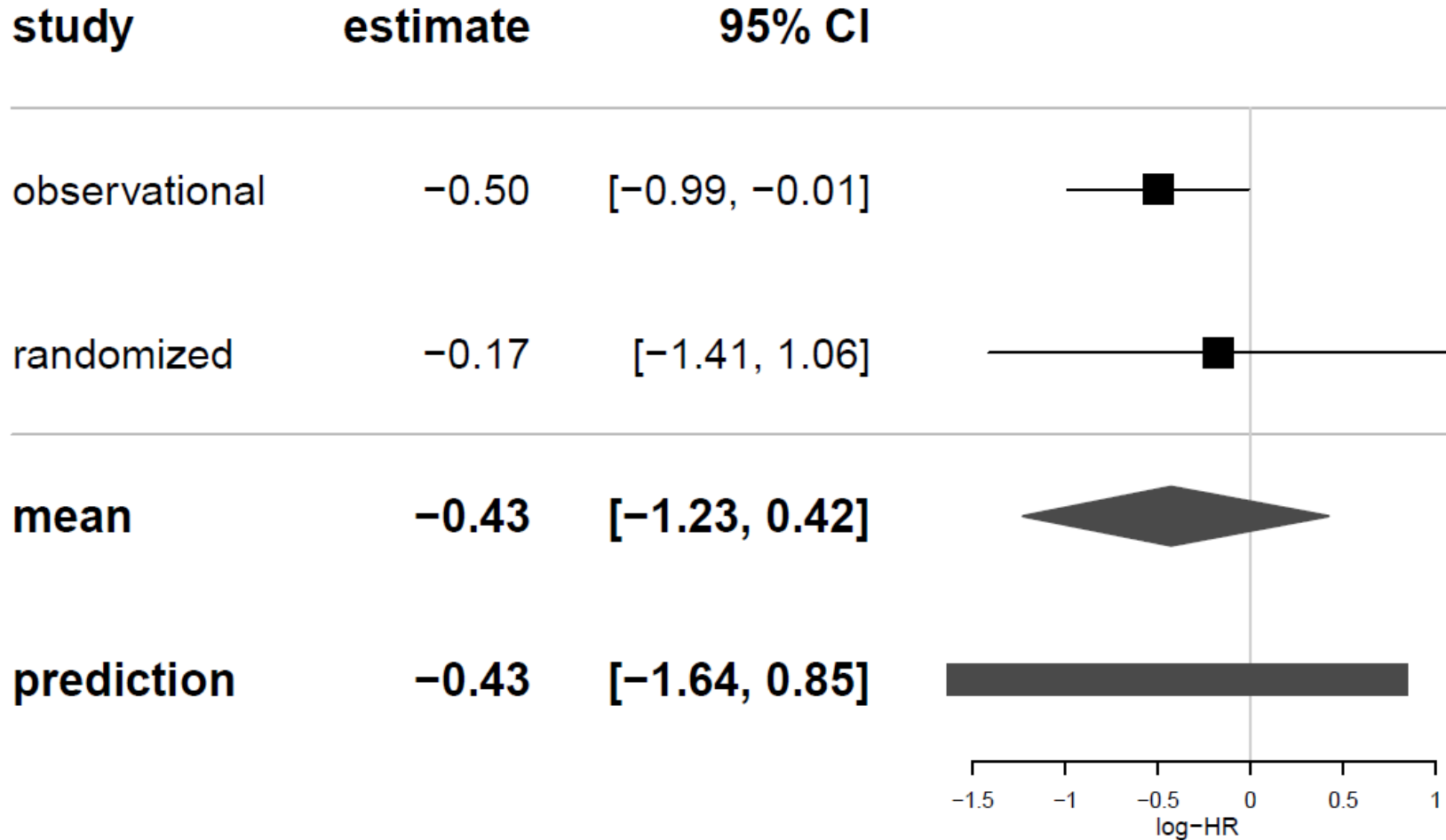
- ▶ prevalence of 1–9 cases per 1,000,000 people
- ▶ qualifies as **rare disease** (EU: less than 5 in 10,000)

## ▶ Varges et al (2016) conducted:

- ▶ double-blinded randomized phase II trial (n=12)
- ▶ observational study (n=88) (Cox regression stratified by terciles of the propensity scores)
- ▶ survival time as primary outcome



# EXAMPLE IN CJD: BAYESIAN RANDOM-EFFECTS META-ANALYSIS



# QUANTITIES OF INTEREST

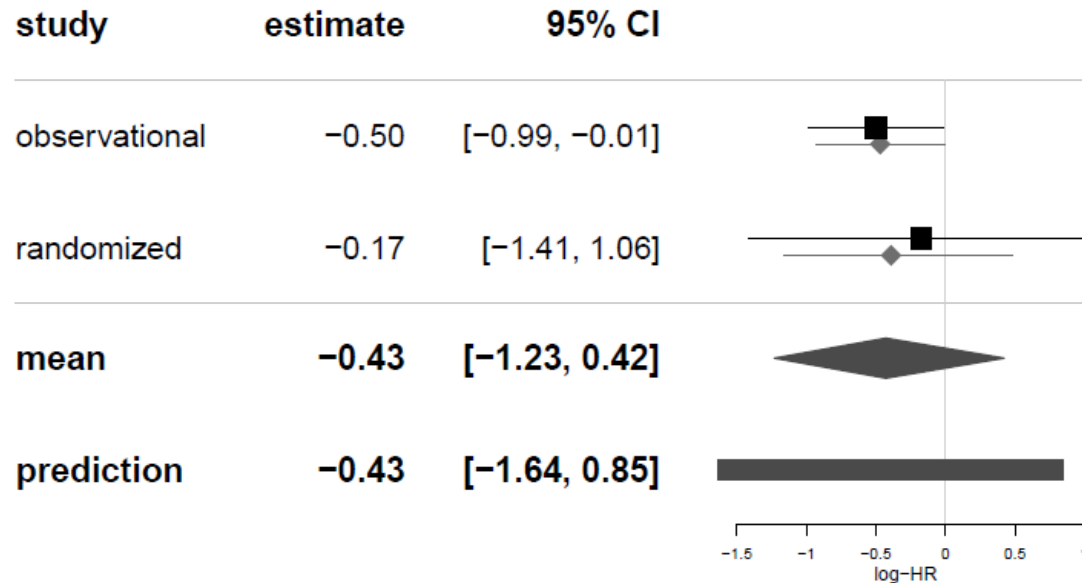
Different quantities of interest in hierarchical models

- ▷ **average effect** ( $\mu$ ) across studies
  - ▷ standard (pairwise) meta-analysis
- ▷ effect ( $\mu_{k+1}$ ) of a future study
  - ▷ **prediction / extrapolation**: adult to children; bridging
- ▷ effect ( $\mu_i$ ) of an individual study in the light of the other studies (**shrinkage estimator**)
  - ▷ small RCT with borrowing from registry

# SHRINKAGE ESTIMATION

- ▷ **Approaches to compute shrinkage estimator**
  - ▷ **Meta-analytic-predictive (MAP) approach:** meta-analyze all but *ith* study; resulting posterior yields meta-analytic predictive (MAP) prior, use MAP prior and data  $y_i$  to infer  $\mu_i$
  - ▷ **Meta-analytic-combined (MAC) approach:** perform joint meta-analysis of all studies, determine *ith* shrinkage estimate
  - ▷ both approaches yield identical results (Schmidli et al (2014) Biometrics)

# EXAMPLE IN CJD: SHRINKAGE ESTIMATOR



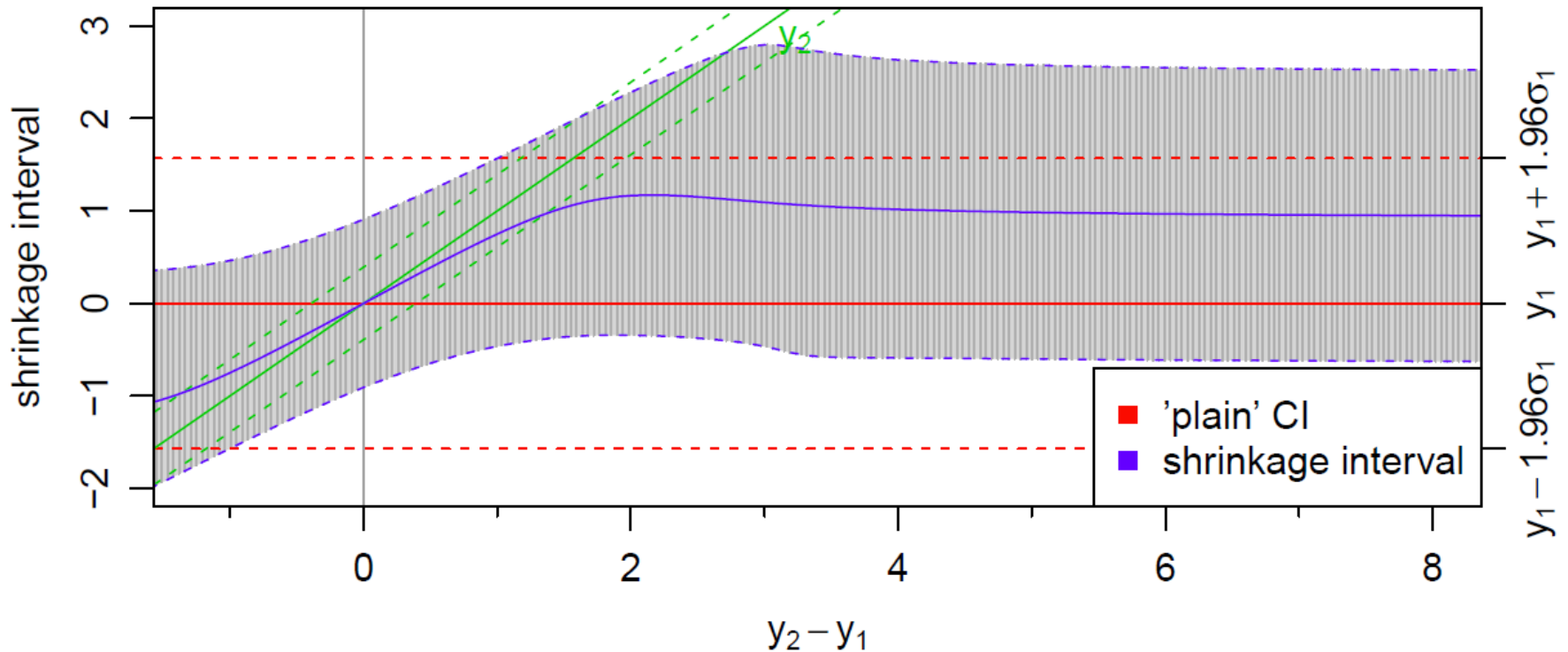
## ▷ Gain in efficiency

- ▷ RCT shrinkage interval width: 66% of original CI width
- ▷ Translates into 129% gain in sample size (about 27 instead of 12 patients)

## ▷ Computations carried out using R package bayesmeta

Röver & Friede (2017) in preparation

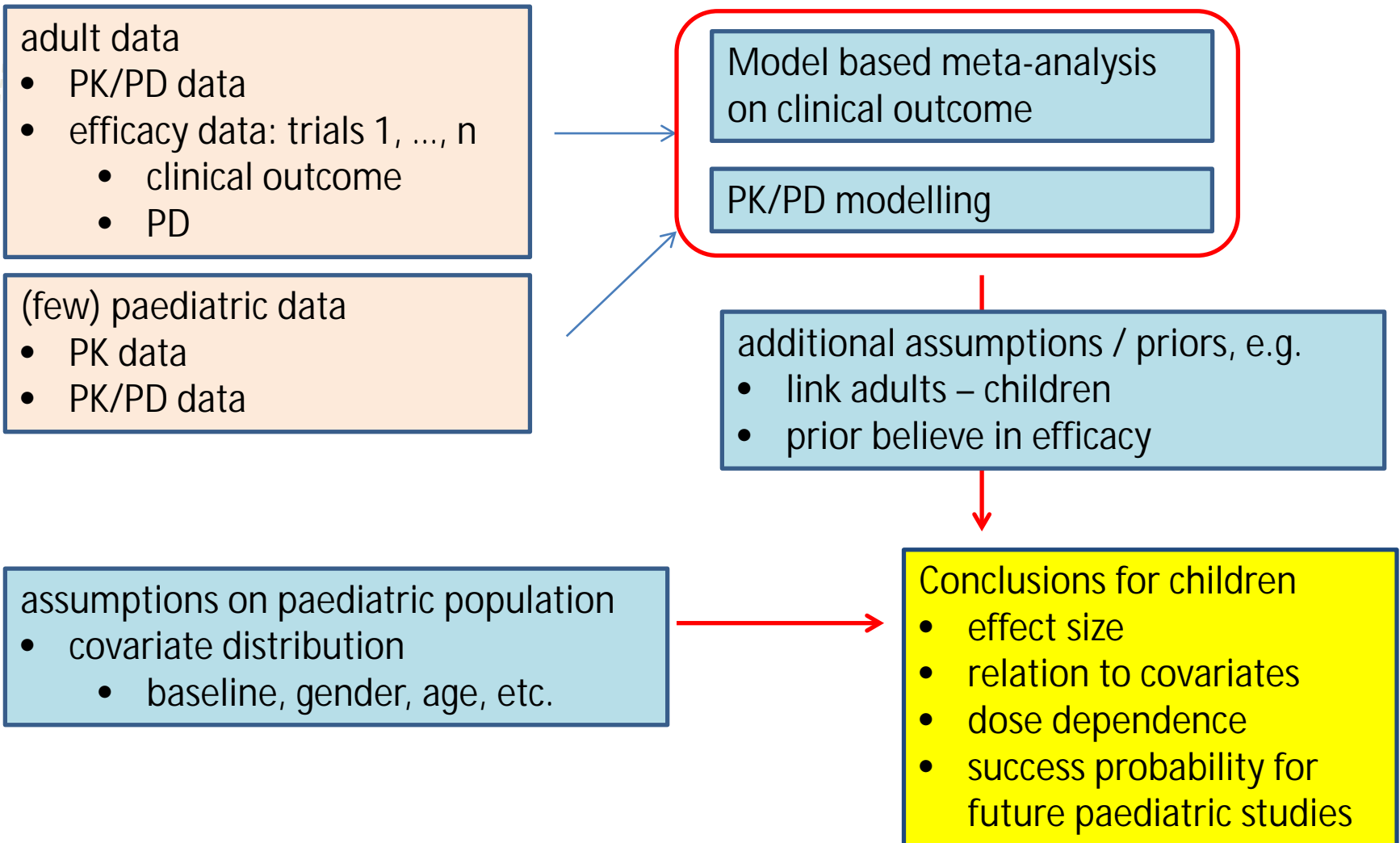
# SHRINKAGE ESTIMATION: EXPLORING ROBUSTNESS IN CSE EXERCISE



- $n_1 = 25$ ,  $n_2 = 400$ ,  $p(\tau) = \text{HN}(0.5)$ , interested in  $\theta_1$

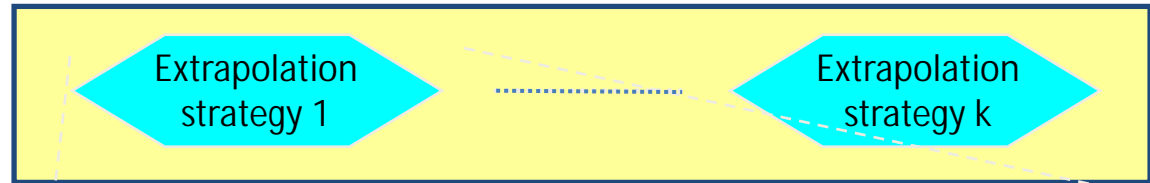


# EXTRAPOLATION STRATEGY (EXAMPLE): ADULTS TO CHILDREN



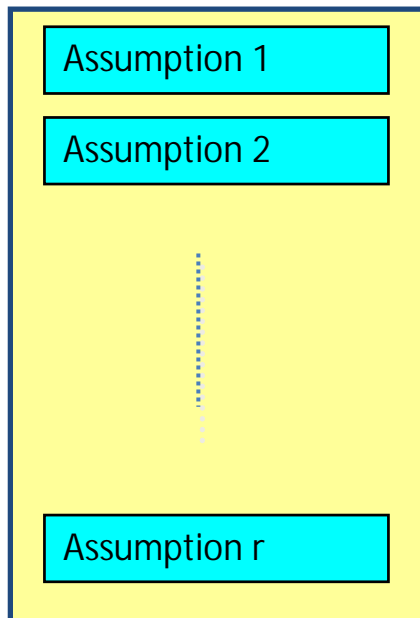
# CSE APPLIED TO EXTRAPOLATION

*Set of different extrapolation strategies*

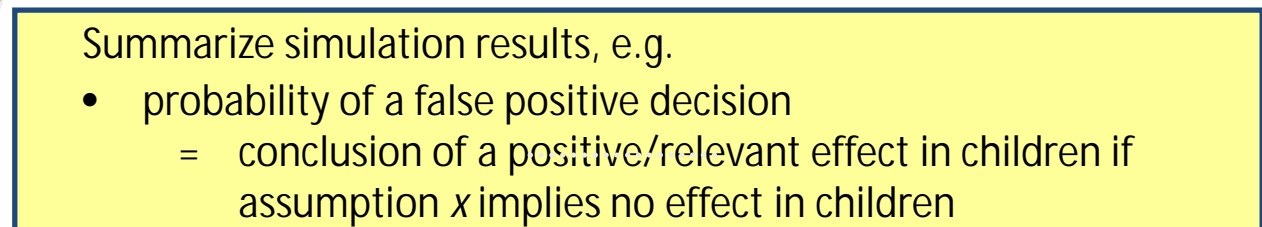
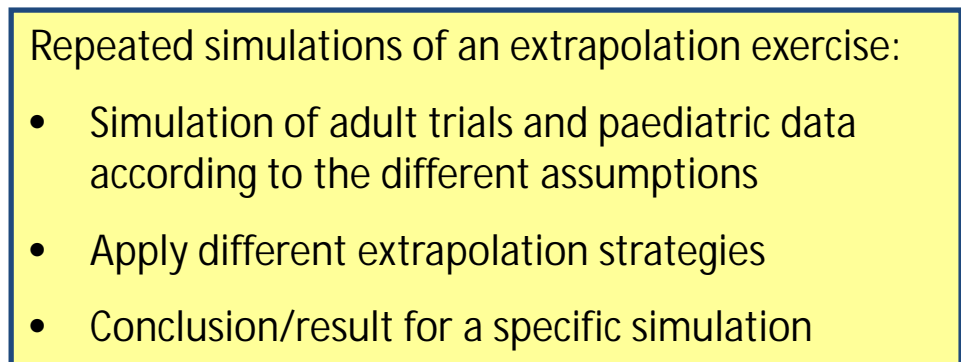


*Assumption set on*

- *adult data*
- *paediatric data*
- *link*



*Clinical Scenario Evaluation*



## DISCUSSION AND CONCLUSIONS

- ▶ Rising **pressure on resources** for clinical trials and **shifting patient populations** lead to increasing **demand for efficient and robust clinical trials**
- ▶ **More complex designs and analysis methods** increase need for **Monte Carlo simulations**
- ▶ **Clinical scenario evaluation framework**
  - ▶ Support structured and early planning
  - ▶ Exploration of efficient approaches
  - ▶ Assessment of robustness
- ▶ **Challenges in small populations and rare diseases**

# SOME REFERENCES

- ▶ Benda N, Branson M, Maurer W, Friede T (2010) Aspects of modernizing drug development using scenario planning and evaluation. *Drug Information Journal* 44: 299-315.
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