



**Cardiovascular medicine: approaches to the use of early biomarker response to identify a patient subgroup with enhanced therapeutic benefit**

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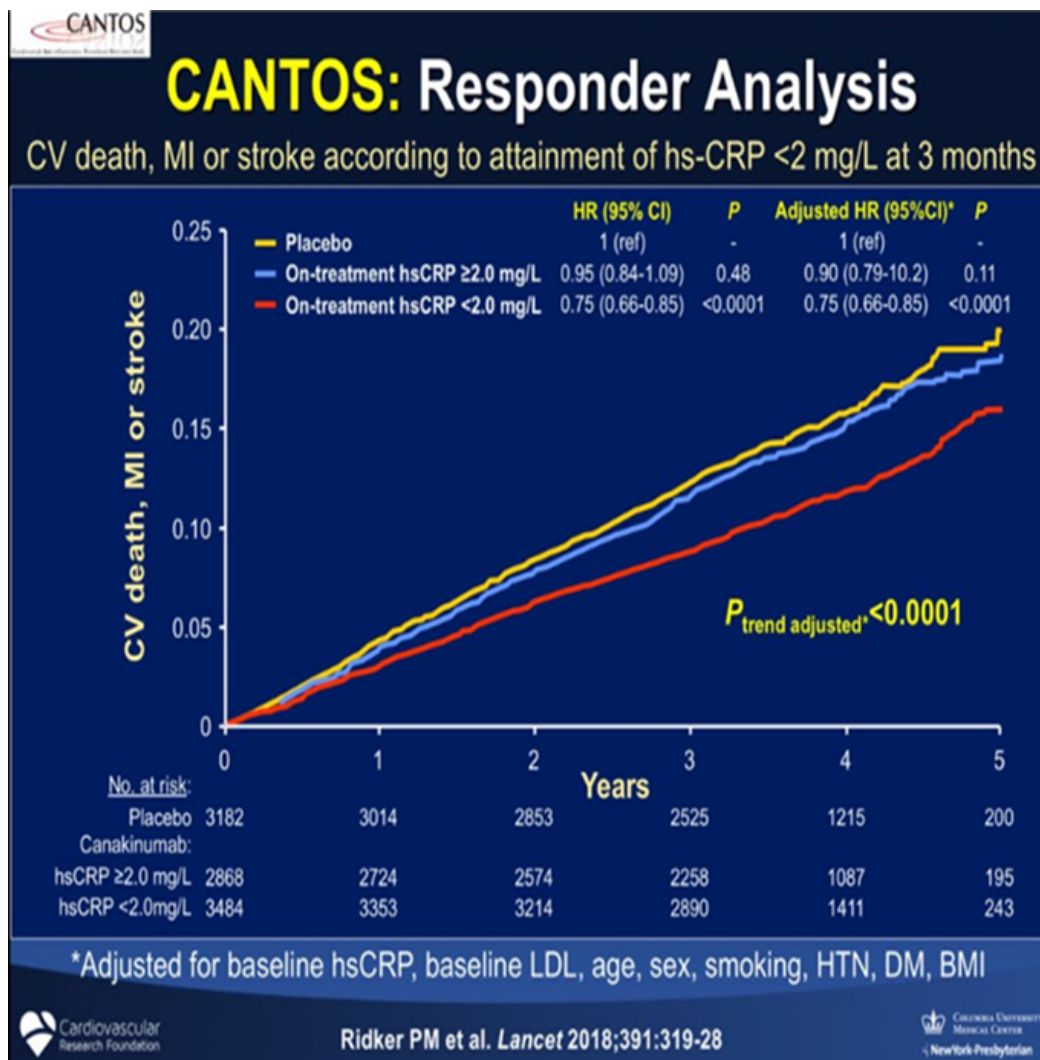
based on [https://doi.org/  
10.1080/19466315.2019.1575280](https://doi.org/10.1080/19466315.2019.1575280)

# Background: the CANTOS trial

- CANTOS trial
  - Tested whether reducing inflammation with canakinumab leads to reduction in the risk of CV events
  - Canakinumab blocks Interleukin-1 $\beta$  (IL-1 $\beta$ ) a cytokine that modulates inflammatory response
    - The downstream marker of inflammatory risk and also of treatment activity was high-sensitivity C-Reactive Protein (hsCRP)
    - Observational data establish that it is prognostic of cardiovascular risk
- Population:
  - previous myocardial infarction and hsCRP > 2 mg per liter
- Treatment
  - Three dosing regimens vs placebo
    - 50mg, 150mg, 300mg every 4 weeks (+ loading for the 300mg group)
- Primary outcome: Time to first major adverse cardiovascular events (MACE)
  - cardiovascular death, nonfatal myocardial infarction, or nonfatal stroke
- Results:
  - Only 150mg significant after adjusting for multiplicity with a hazard ratio of 0.85

# Responder subgroup in the CANTOS trial

- It suggested a larger benefit in this subpopulation than in the overall trial population
- The comparison implemented compared responders pooling all 3 canakinumab groups, to all placebo regardless of their month 3 hsCRP levels



# What is the estimand that captures the effect of treatment?

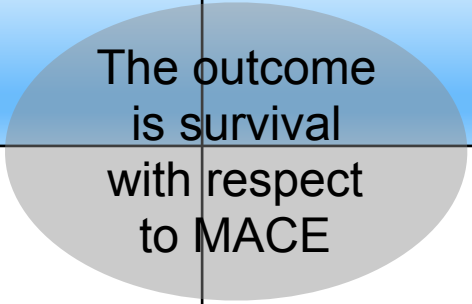
- Estimand: Treatment effect on MACE in the population of patients that would at month 3 reach hsCRP < 2.0 mg/L if assigned to treatment
- Attainment of hsCRP levels < 2 mg/L on active treatment is an event arising post-randomization
- Identification of this estimand requires strong assumptions in a parallel groups trial
  - Not immediately clear how survival for treatment threshold achievers would have been if treated with placebo
  - & vice versa which patients on placebo would have achieved the threshold if they had received treatment

# Principal stratification estimand

**Z** - indicator of treatment assignment (0: Placebo, 1:Active)

**B(z)** -potential biomarker outcome for treatment  $Z=z$

**T(z)** –Survival outcome on treatment  $z$









|  | Placebo<br><b>B(0) = 1</b><br><i>hsCRP &lt; 2mg/dL</i>  | Placebo<br><b>B(0) = 0</b><br><i>hsCRP ≥ 2mg/dL</i> |
|--|---|---|
| Treatment<br><b>B(1) = 1</b><br><i>hsCRP &lt; 2mg/dL</i> | <br>The outcome is survival with respect to MACE |   |
| Treatment<br><b>B(1) = 0</b><br><i>hsCRP ≥ 2mg/dL</i>    |   |   |

- Subpopulation of interest
  - Patients with  $B(1) = 1$  (threshold achievers on treatment)
- Quantities of interest to estimate
  - Survival for treatment threshold achievers on treatment  
 $P(T(1) > t \mid B(1) = 1)$
  - **Survival for treatment threshold achievers on placebo**  
 $P(T(0) > t \mid B(1) = 1)$

# Potential outcomes

- Each patient has 2 potential outcomes related to treatment assignment
  - Biomarker levels on treatment,  $B(1)$  and on placebo  $B(0)$
  - Survival on treatment,  $T(1)$ , and survival on placebo  $T(0)$
- In a parallel arm clinical trial only one of these combinations can be observed



|            | $B(0) = 1$   | $B(0) = 0$   |
|------------|--|--|
| $B(1) = 1$ | $T(1)$ $T(0)$<br>    | $T(1)$ $T(0)$<br>    |
| $B(1) = 0$ | $T(1)$ $T(0)$<br>  | $T(1)$ $T(0)$<br>  |

## Identification and estimation:

$$P(T(0) > t \mid B(1) = 1)$$

- Requires additional assumptions:  $T(0) \perp B(1) \mid X$
- We utilize covariates  $X$  predictive of  $T(0)$  and  $B(1)$

by conditional independence



Obtain averaged  
placebo survival of  
treatment responders  
using their covariates

Predict placebo survival for responders on treatment



# Identification and estimation:

## $P(T(0) > t \mid B(1) = 1)$

- Using the same assumptions:  $T(0) \perp B(1) \mid X$
- We utilize covariates  $X$  predictive of  $B(1)$

$dX$

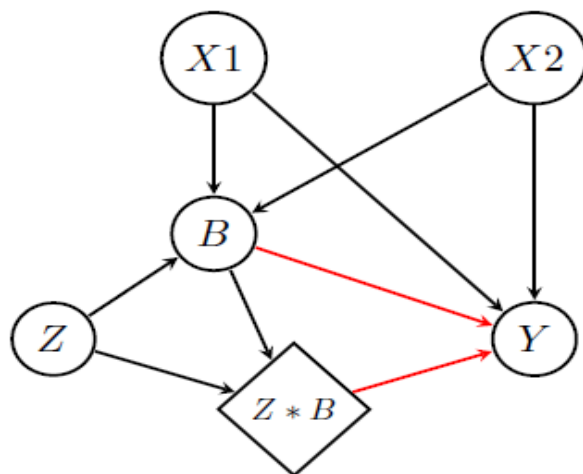
Compare to observed placebo survival weighting placebo patients with



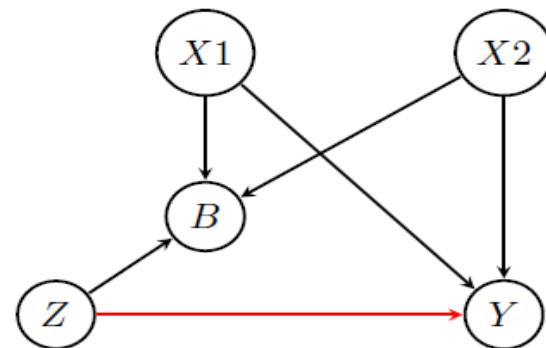
# Simulation experiment to evaluate performance

- Survival outcome trials from
  - Biomarker values ( $Z$ ,)
  - Survival outcomes with
- We evaluate 3 Scenarios

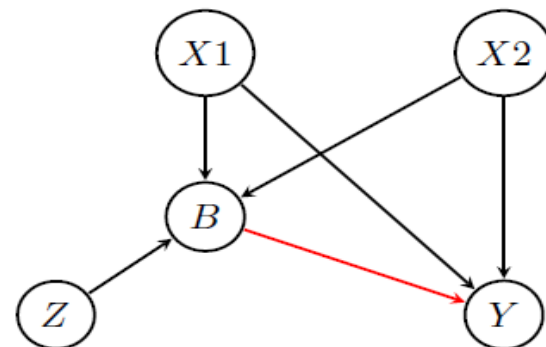
Scenario 3



Scenario 1



Scenario 2



# Issue of the measure for survival outcomes

- The simulations evaluate the **difference in restricted mean survival time (RMST)**
- Reluctance to use the hazard ratio was due to
  - non-collapsibility
  - lack of causal interpretation specifically of the estimate from Cox regression even in a randomized clinical trial (Aalen et al 2015).
- However, we mention that
  - *if the cumulative hazard functions are approximately linear, a simple exponential model could be derived to estimate the hazard, and calculate the hazard ratio as the ratio of the hazards.*
- Main difference:
  - A difference in survival can be estimated non-parametrically (e.g. using the difference in RMST)
  - The hazard rate requires additional modelling assumptions to obtain a single estimate that represents the average hazard rate used to calculate the ratio between treatments

# Performance evaluation

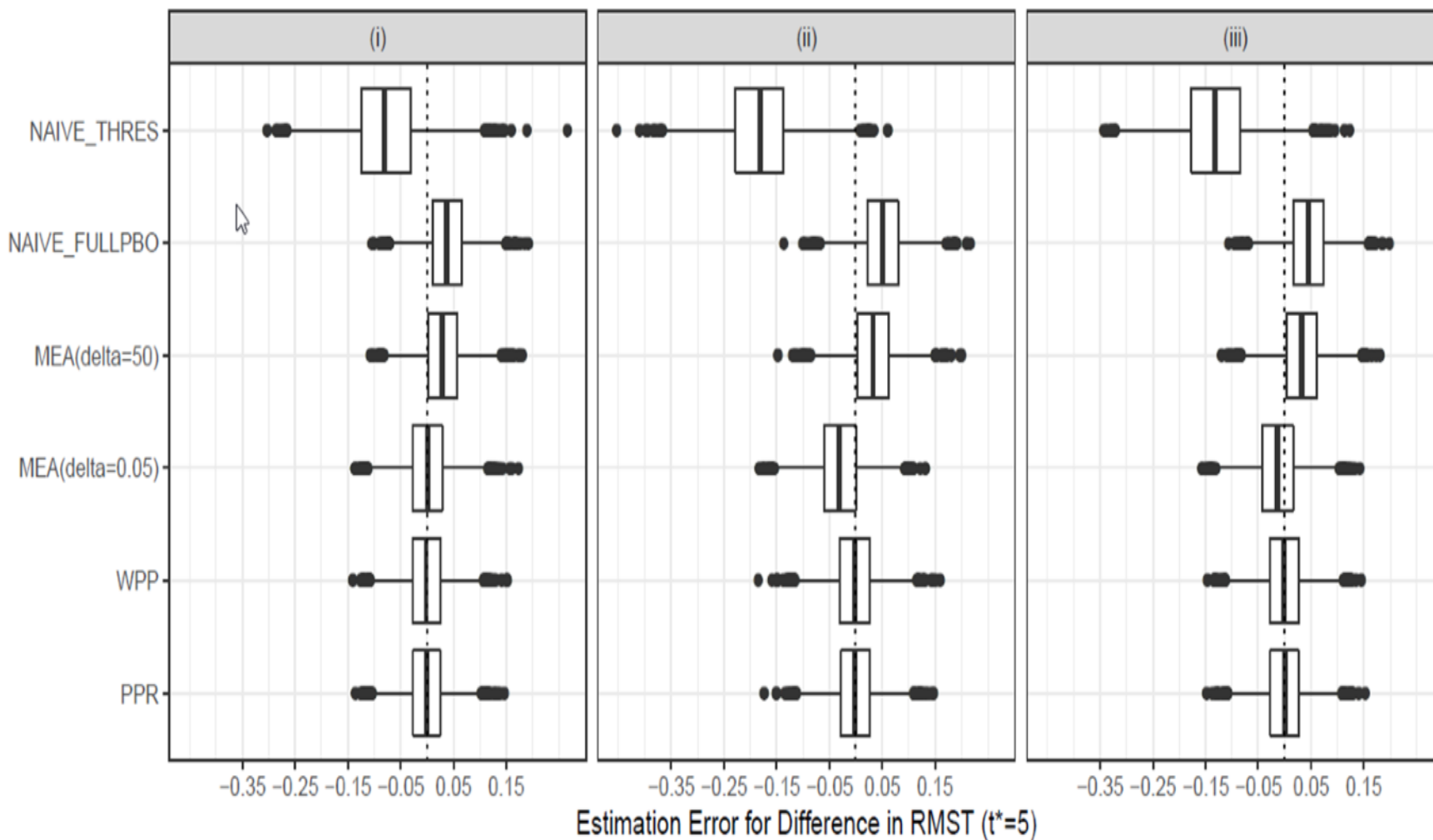
- **Comparison of survival:**
  - *Predicted Placebo Response (PPR)* and *Weight Placebo Patients (WPP)* difference in restricted mean survival time at a pre-specified time point
- **Comparison based on the hazard rates:**
  - *Predicted Placebo (PP)*
    - Same as survival for PPR above. We use a nonlinear regression fit to the survival functions that follows an exponential or Weibull parametrization, and fitting a weighted linear regression model to the cumulative survival function
  - *Weight Placebo (WP)*
    - With weighted Cox regression including treatment only, and X1 and X2 (DR)
- We also compare with 2 “naive” approaches:
  - NAIVE\_THRES- compares to placebo patients reaching the threshold (on placebo)
  - NAIVE\_FULLPBO- compares to all placebo patients regardless of whether they would have been responders if given treatment or not

# Results: survival difference scale

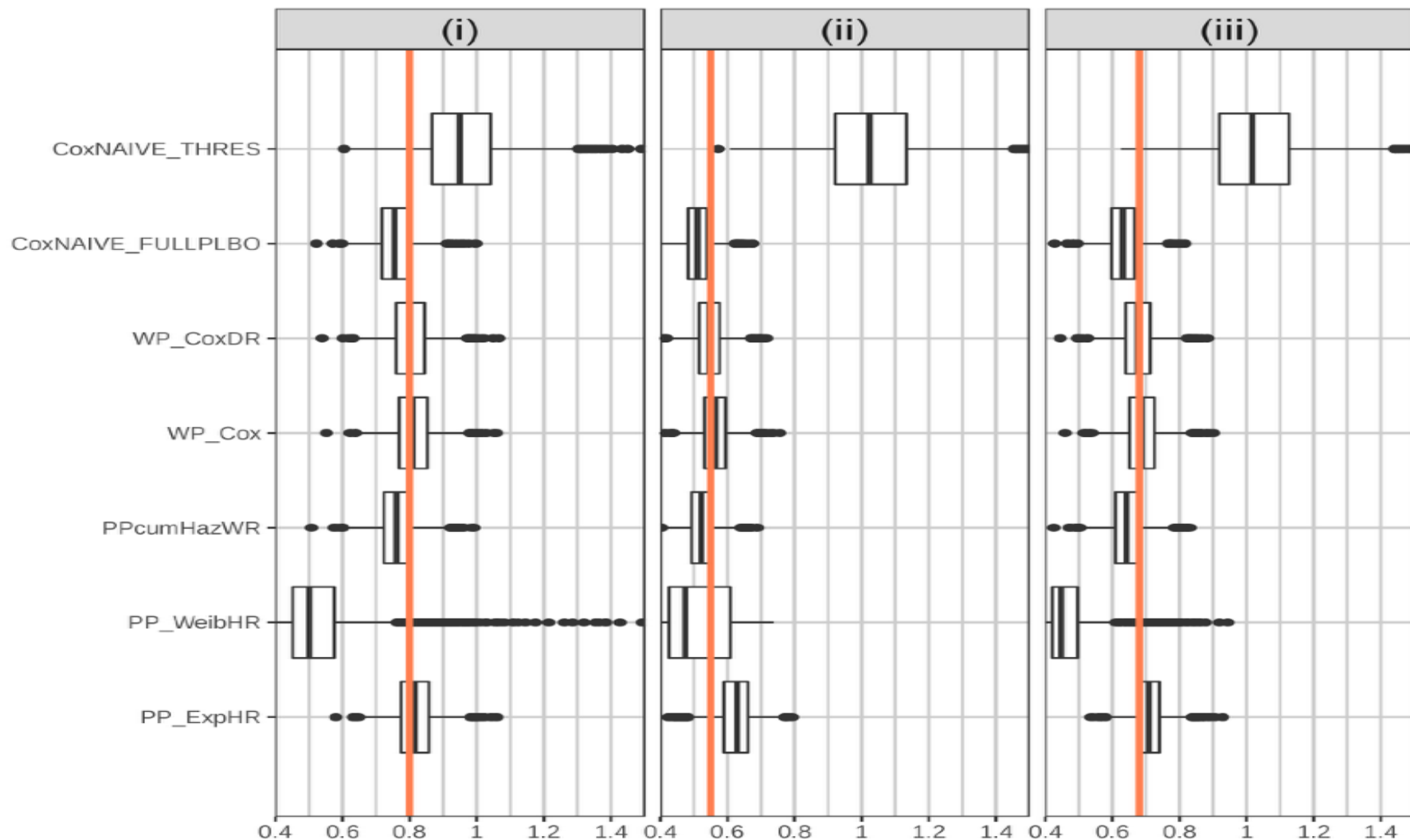
(i) Only main effect of Z

(ii) Only main effect of B

(iii) Main effect of B and  $Z * B$



# Results: hazard ratio scale



# Summary

- These are approaches to derive the magnitude of treatment benefit in a patient subpopulation defined by an early biomarker response
  - They are not meant as mediation analysis
  - They do not fall in the surrogacy field
  - We do not account for inter-current events. Their treatment requires additional assumptions.
  - We keep **survival risk between treatments equal to risk at the time of randomization assuming all patients have biomarker measurements**
- **Survival difference scale:** both approaches perform well regardless of the path through which treatment impacts survival
- **Hazard ratio scale:** only the weighted placebo applied to Cox regression including covariates performs well regardless of treatment path

# Is this useful for cardiovascular drug development?

- An early response to treatment can be used for treatment optimization strategies or treatment selection
  - This framework cannot replace a randomized comparison, but may be useful for planning future targeted randomized trials
- Cardiovascular outcome trials build on the premise of homogeneous patient responses
  - but the long treatment horizon with competing events dilutes treatment impact in some patient segments
  - This causal inference framework can enhance understanding of patient responses
  - Protocol defined follow up treatment strategies might be a way of optimizing the conduct of these trials