



Applying prognostic scoring adjustments to enhance clinical trial efficiency in neurodegenerative diseases

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Covariate Adjustment

Simulation (repeated x1000)

Standard RCT design considerations:

- ❖ Provide high power to test whether a treatment effect exists
- ❖ Provide reasonable precision to characterize the treatment effect
- Outcome =
treatment or control \pm
prognostic covariate(s)

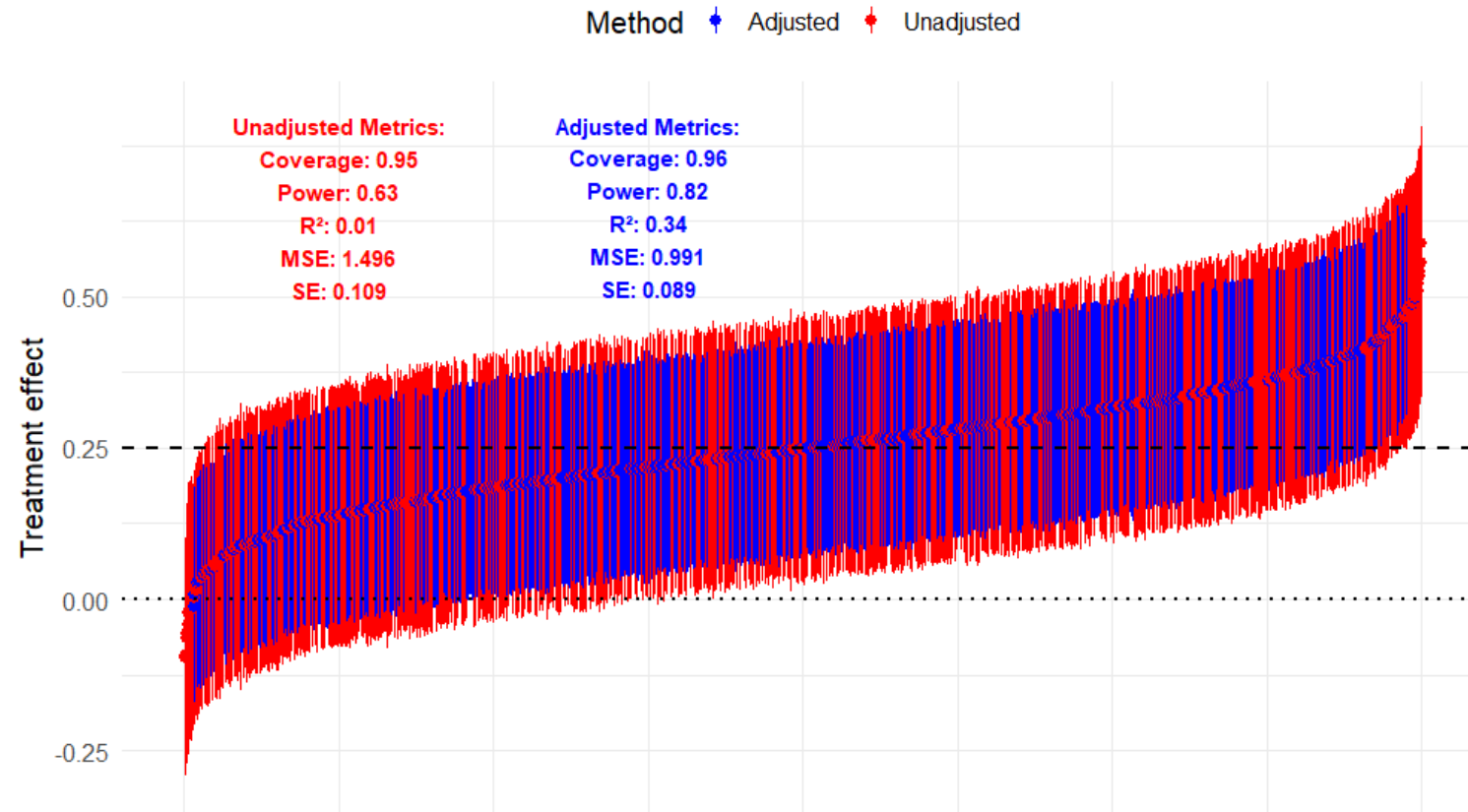
$$Y_i = \beta_0 + \beta_1 \times \text{Treatment}_{0 \text{ or } 1} + \epsilon_i$$

or

$$Y_i = \beta_0 + \beta_1 \times \text{Treatment}_{0 \text{ or } 1} + \beta_2 \text{Age}_i + \dots + \beta_n \text{PC}_{ni} + \epsilon_i$$

$$Y|X, T \sim N(\mu = 0.25 \times \text{Treatment}_1 + 0.5X_1 + 0.3X_2 + 0.2X_3, \sigma^2 = 1)$$

Waterfall plot of estimated treatment effects



Digital Twin Workflow



Step 1

Use observed patient characteristics (e.g., demographics, biomarkers) from external data sources.



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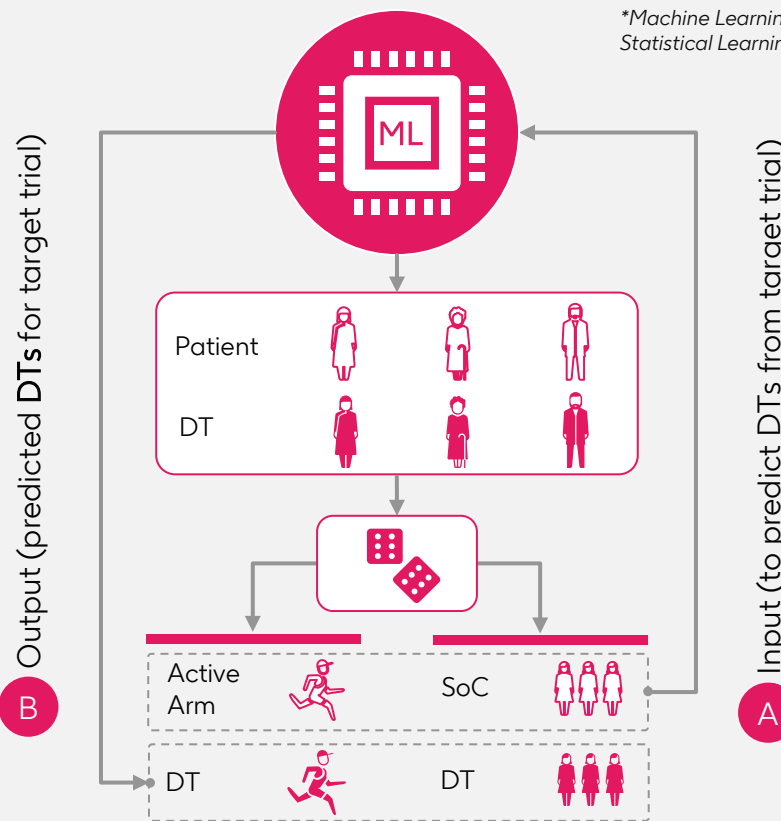
Use observed patient characteristics (e.g., demographics, biomarkers) from external data sources.



Step 2

Train an ensemble of ML/SL* models on external data to predict outcomes based on standard of care. Apply these models to baseline characteristics of trial patients to create a personalised digital twin for each patient, predicting their likely outcome.

**Machine Learning/
Statistical Learning*



Step 1

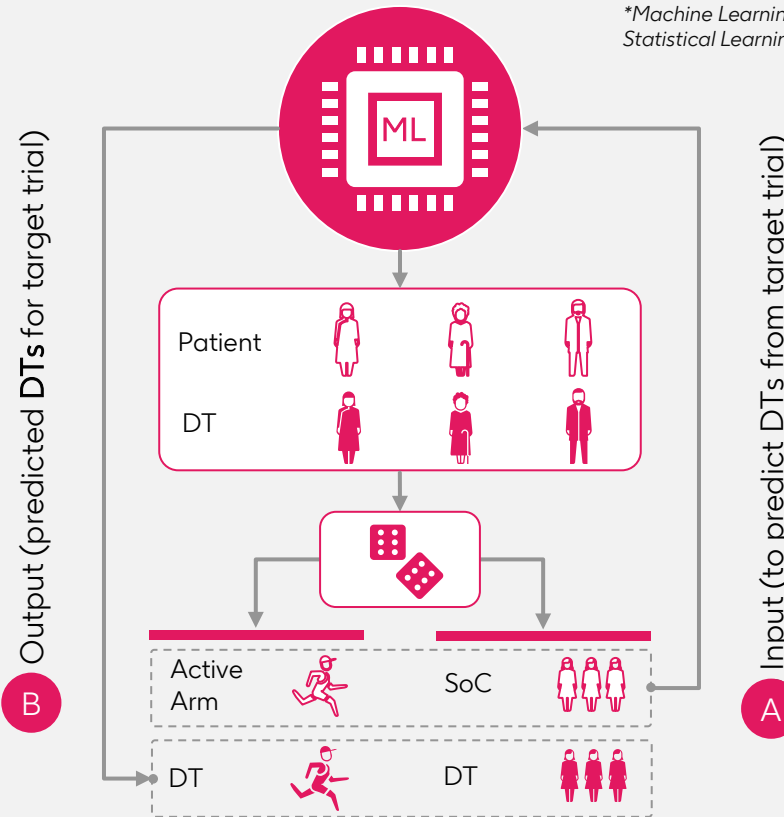
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Step 3

Integrate the digital twin prediction as a 'super-covariate' into the trial's analysis model to enhance study power.

Outcome =	Average treatment effect	+	Prognostic covariates	+	DT 'super-covariate'
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Impact on trial design in terms of expected power gains / reduced sample sizes:

- Improvements of power of 5%+ can be expected
- Reductions of sample size (SS) of 10-30+% are reasonable

Regulatory positions – FDA & EMA

Relevant commentary from the regulators on covariate adjustment and its value



Adjusting for
Covariates in
Randomized Clinical
Trials for Drugs and
Biological Products
Guidance for Industry



III. RECOMMENDATIONS FOR COVARIATE ADJUSTMENT IN CLINICAL TRIALS

“Covariate adjustment leads to efficiency gains when the covariates are **prognostic** for the outcome of interest in the trial. Therefore, FDA recommends that sponsors adjust for **covariates that are anticipated to be most strongly associated with the outcome of interest**. In some circumstances these covariates may be known from the scientific literature. In other cases, it may be useful to **use previous studies** (e.g., a Phase 2 trial) to select prognostic covariates or **form prognostic indices**.”



Using Artificial Intelligence
& Machine Learning
in the Development of
Drug & Biological Products

Discussion Paper and Request for Feedback



“At an even more personalized level, AI/ML can also be used in the context of **digital twins** of patients, an emerging method that could potentially be used in clinical research. To create digital twins of patients, **AI/ML can be utilized to build in silico representations or replicas of an individual** that can dynamically reflect molecular and physiological status over time (European Medicines Agency, 2022; Laubenbacher, Sluka, & Glazier, 2021; Schuler et al., 2021). [...] the digital twin could potentially provide a comprehensive, longitudinal, and computationally generated **clinical record that describes what may have happened to that specific participant if they had received a placebo**.”



20 September 2022
EMA/DOC-1700519818-907465
Committee for Medicinal Products for Human Use (CHMP)

Qualification opinion for Prognostic Covariate Adjustment
(PROCOVA™)

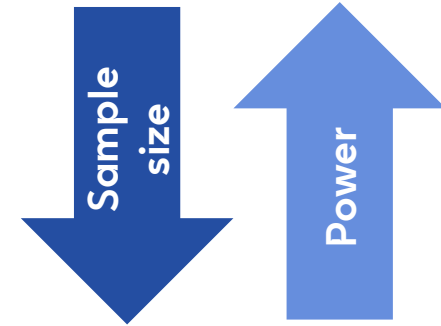


“CHMP qualifies PROCOVA as **prognostic score adjustment** and the proposed procedures, as described in a handbook for trial statisticians, **could enable increases in power or precision of treatment effect estimates** in controlled randomised clinical trials with continuous outcomes. ... Approaches with **non-linear models for analysis** and direct comparisons to such models, as well as models with treatment-by-covariate interactions **are out of scope of this qualification procedure**.”

Draft agreed by Scientific Advice Working Party (SAWP)	10 February 2022
Adopted by CHMP for release for consultation	24 February 2022 ¹

Prognostic scores in MMRM

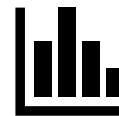
Leverage baseline measurements and/or external data sources



*Reduce sample size and/or increase power
to detect average treatment effects*



Model misspecification



Covariate selection & dimensionality



Nonlinearity

MMRMs

- For RCTs with continuous longitudinal outcomes
- Special case of ANCOVA

$$Y_{ij} = \beta_0 + \underbrace{\beta_1 W_i}_{=\text{treatment}} \times \text{Time}_{ij} + \underbrace{\beta_2 \text{Age} + \beta_3 \text{sex} + \dots + \beta_n \text{PC}_n}_{=\text{prognostic score, } m(x)}$$

Y_{ij} continuous outcome for patient i , j timepoint, i.i.d $N(\mu_W, \sigma^2)$ for treatment $W=0$ or 1

Prognostic score $m(\cdot)$ computed on baseline covariates X_i for patient i

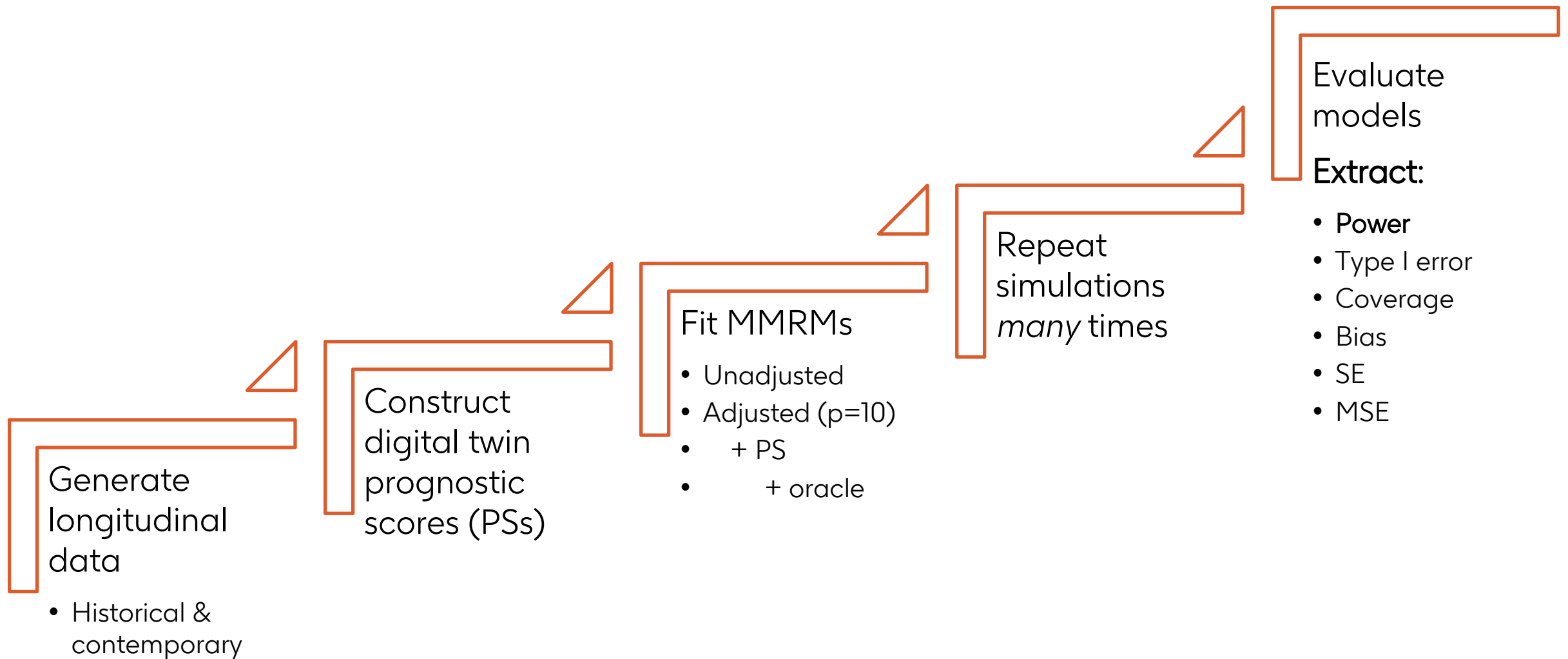
$$= \beta_0 + \beta_1 W_i \times \text{Time}_{ij} + \beta_2 m(X_i) + \epsilon_i$$

Treatment indicator (W_i) for patient i , $W_i = 0, 1$

- Inherits ANCOVA properties: unbiasedness, control of type I error
- Variance reduction increases with increasing correlation between predictor $m(X)$ and outcome Y
- Sophisticated AI models may more closely represent functional relationship between X and Y
- Out of scope: non-GLM models $Y \sim f(m(X))$ and models with treatment-by-covariate interactions (non constant effects)

Simulation study

Overview



Simulations to assess performance and robustness to assumptions

4 data-generation scenarios

1. The **Linear simulation scenario**: the conditional average effect is $E[Y_1 - Y_0|X]$, the outcome-covariate relationship is linear in both the active and control treatment arms with a constant treatment effect.
2. The **homogenous & non-linear simulation scenario**: the outcome-covariate relationship is non-linear in both treatment arms, but the treatment effect is constant
3. The **Heterogeneous simulation** not constant (i.e., $E[Y_1 - Y_0|X] \neq \mu_1(X) - \mu_0(X)$).
4. The **Shifted simulation scenario**: the historical population used to train the prognostic model is not representative of the trial population in terms of the baseline covariates (i.e., $P_H(X' = x) \neq P(X = x)$).

PS covariate-
adjustment
assumptions
met

Assumptions
violated*

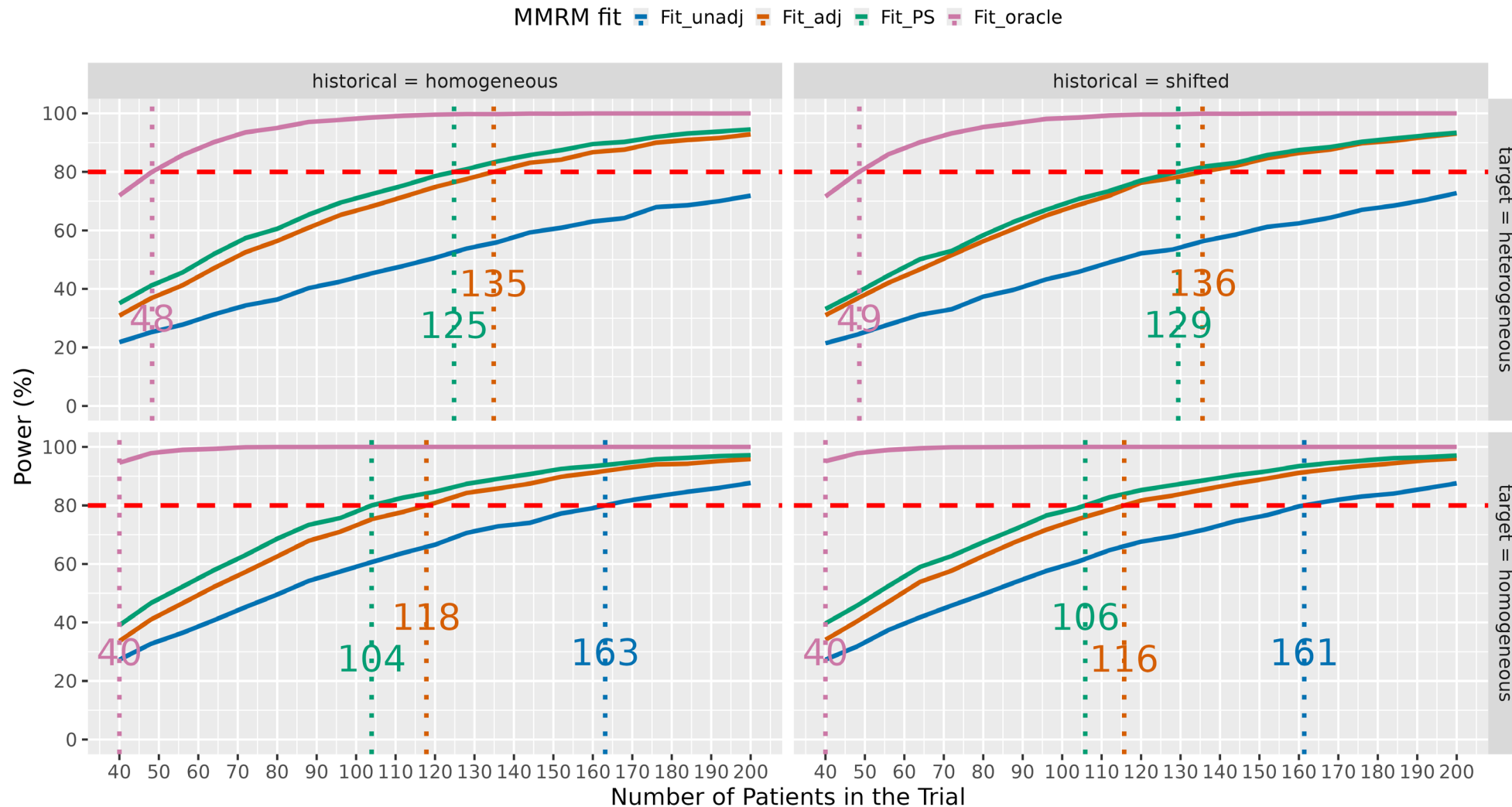
Lack of external
validity

*: If the treatment effect is constant, then the optimal covariate to adjust for in ANCOVA is a prediction of the potential control outcome for a subject, based on that subject's observed baseline covariates.

Results

Comparison of Five MMRM Models: Treatment Effect = -1.2

$Fit_unadj: mrm(Y \sim time * treatment + us(time | id);$
 $Fit_adj: mrm(Y \sim time * treatment + us(time | id) + (X1 + \dots + X10) ;$
 $Fit_PS: mrm(Y \sim time * treatment + us(time | id) + estimated\ Prognostic\ Score\ (ePS);$
 $Fit_oracle: mrm(Y \sim time * treatment + us(time | id) + true\ Prognostic\ Score\ (tPS)$



10000 simulations; historical dataset is homogeneous with 5000 patients

Take homes & continued work

- We've demonstrated the benefit, in the presence of prognostic scores, the additional power gain when leveraging historical data to inform your target trial
- This has been further extended in longitudinal study setting (e.g. neurodegenerative diseases)
- **Leading to sufficiently powered trials → maximizing PoS**

Future considerations

- Including additional biomarkers, and assess the trade-off between a reduction in SS and model improvement
- Better quantify the expected precision / power gain using the relationship of the ML model & its correlation
- Extend to pMMRM analysis models for additional PoS gains.

Bibliography

- Adjusting for Covariate in Randomized Clinical Trials for Drugs & Biologics (FDA, May 2023)
- S. Siegfried et al., *Biom. J.* **65** (2023).
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