

Statistical Methods for Innovative Platform Trial Designs Incorporating Non-concurrent Controls

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Multi-arm multi-stage trials that allow new experimental treatment arms to enter and leave the trial at different times.¹

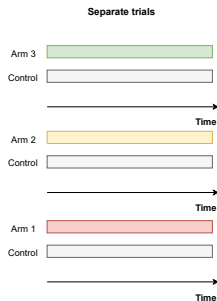
- Treatments to be studied not defined upfront
- Control arm can be shared

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Adaptive platform trials

Multi-arm multi-stage trials that allow new experimental treatment arms to enter and leave the trial at different times.¹

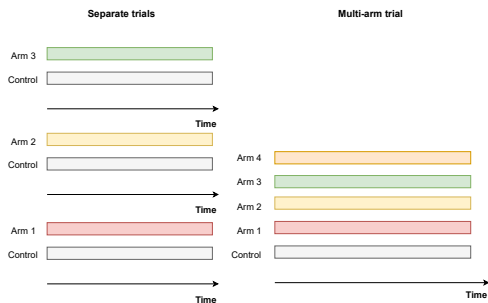
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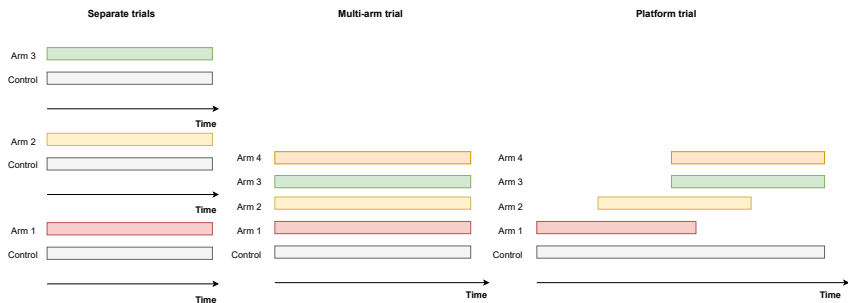


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Adaptive platform trials

Benefits:

- Treatments are evaluated **faster** as compared to separate trials since drugs are tested **in parallel**
- Trials are **more efficient** due to the joint trial infrastructure
- **Less patients** are required in the control group as it is shared across all treatment arms
- Experimental treatments can enter the trial as they become available, which provides **more flexibility** than multi-arm trials

Adaptive platform trials

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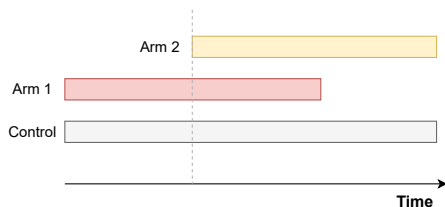
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Challenges:

- Multiple operational and statistical challenges due to **higher complexity**
- Adaptations to the trial (e.g. entering and leaving times or the total number of experimental treatments) are **unknown in advance**
- Use of the **shared control arm** in trial analysis

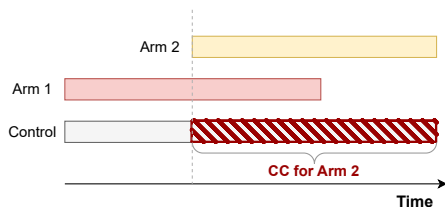
Concurrent and non-concurrent controls

- **Concurrent controls (CC):** patients recruited to the control when the experimental treatment is part of the platform
- **Non-concurrent controls (NCC):** patients recruited before the experimental treatment entered the platform



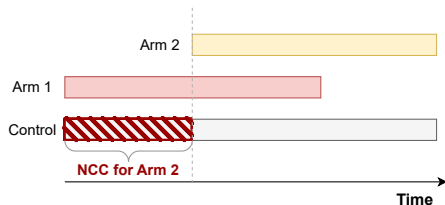
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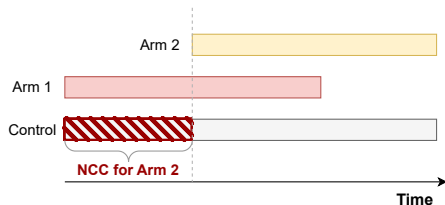
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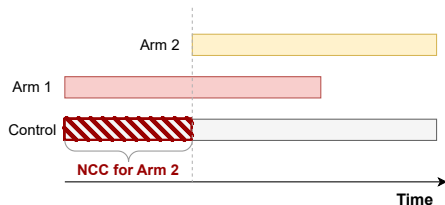
Hypothesis testing problem:

$$H_0 : \theta_2 = 0$$

$$H_1 : \theta_2 > 0$$

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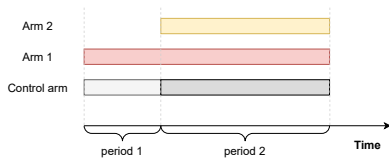
$$H_1 : \theta_2 > 0$$

Challenges when using NCC in the presence of time trends²:

- Bias in the estimates
- Type I error rate control

²Dodd, L. E., et al. (2021). Platform Trials — Beware the Noncomparable Control Group. New England Journal of Medicine.

State-of-the-art analysis methods

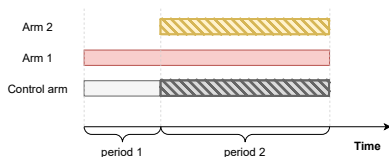


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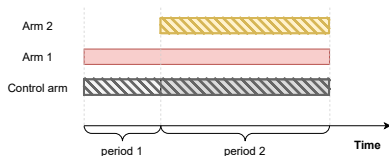
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Simple analysis methods

- **Separate approach:** analysis using only concurrent controls

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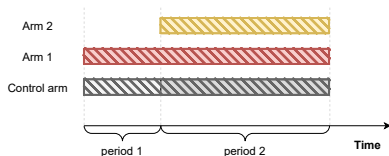
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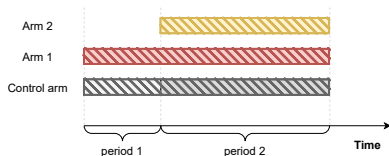
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Modelling approaches with time trend adjustment

- **Frequentist regression models:** adjust for time trends by including the factor period as a fixed effect (Lee & Wason, 2020; Bofill Roig, Krotka, et al., 2022)
- **Bayesian Time Machine:** adjusts for time by smoothing over calendar time intervals with a Bayesian normal dynamic linear model (Saville, et al., 2022)

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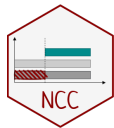
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NCC R-package

- Software implementation of methods for incorporating NCC (Krotka, et al., 2023)
- Accompanying website: <https://pavlakrotka.github.io/NCC/>



Goals of the PhD thesis

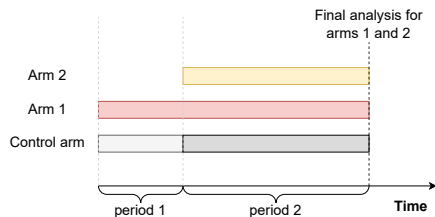
1. Methodology for incorporating non-concurrent controls in trials with continuous endpoints and interim analyses
2. Extension of the methodology for including non-concurrent controls to trials with time-to-event endpoints
3. Methods for adaptive group-sequential trial designs utilizing pseudo-values regression
4. Software implementation in the NCC R-package

Objective 1

Incorporating non-concurrent controls in trials with interim analyses

Frequentist regression model

Without interim analysis in arm 1



Hypothesis testing problem:

$$H_0 : \theta_2 = 0$$

$$H_1 : \theta_2 > 0$$

Model-based approach³ based on data from all treatment arms and control:

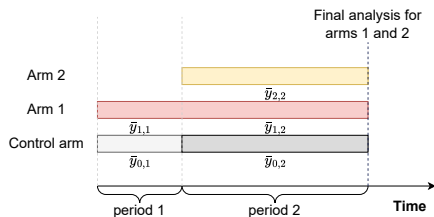
$$E(y_j) = \underbrace{\eta_0}_{\text{Control response in period 1}} + \underbrace{\sum_{k=1,2} \theta_k \cdot I(k_j = k)}_{\text{Treatment effects}} + \underbrace{\tau \cdot I(s_j = 2)}_{\text{Period time effect}}$$

where y_j is the outcome, $k = 0, 1, 2$ denotes the treatment and $s = 1, 2$ the period.

³Bofill Roig, M., Krotka, P., et al. (2022). "On model-based time trend adjustments in platform trials with non-concurrent controls." BMC Medical research methodology.

Estimation of treatment effect in arm 2 using regression methods

Without interim analysis in arm 1



$$\rho = \frac{\frac{1}{n_{0,2}}}{\frac{1}{n_{0,1}} + \frac{1}{n_{0,2}} + \frac{1}{n_{1,1}} + \frac{1}{n_{1,2}}}$$

Treatment **effect estimator** using the model-based approach:

$$\tilde{\theta}_2 = \bar{y}_{2,2} - \tilde{y}_{0,2}$$

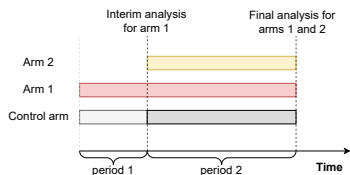
Model-based estimate of the **control response** in period 2:

$$\tilde{y}_{0,2} = (1 - \rho) \cdot \bar{y}_{0,2} + \rho \cdot [\bar{y}_{0,1} + \underbrace{(\bar{y}_{1,2} - \bar{y}_{1,1})}_{\text{Time trend estimate}}]$$

Model-based approach leads to an **unbiased treatment effect estimator** $\tilde{\theta}_2$ if the time trends in all arms are equal and additive on the model scale.

Platform trials with group sequential interim analyses

Interim analysis in arm 1 at the entry time of arm 2



Hypothesis testing problem:

Arm 1:

$$H_0 : \theta_1 = 0$$

$$H_1 : \theta_1 > 0$$

Interim analysis of arm 1:

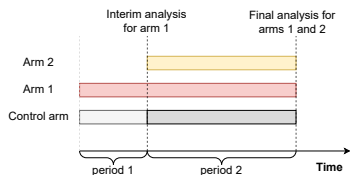
Linear regression model without time adjustment:

$$E(y_j) = \underbrace{\eta_0}_{\text{Control response}} + \underbrace{\theta_1 \cdot I(k_j = 1)}_{\text{Treatment effect}}$$

- Stop arm 1 for futility if the one-sided p-value $p > \alpha_1$

Platform trials with group sequential interim analyses

Interim analysis in arm 1 at the entry time of arm 2



Hypothesis testing problem:

Arm 1:

$$\begin{aligned}H_0 &: \theta_1 = 0 \\H_1 &: \theta_1 > 0\end{aligned}$$

Arm 2:

$$\begin{aligned}H_0 &: \theta_2 = 0 \\H_1 &: \theta_2 > 0\end{aligned}$$

Interim analysis of arm 1:

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- Stop arm 1 for futility if the one-sided p-value $p > \alpha_1$

Analysis of arm 2:

Model-based approach including non-concurrent controls and adjusting for periods:

$$E(y_j) = \underbrace{\eta_0}_{\text{Control response in period 1}} + \underbrace{\sum_{k=1,2} \theta_k \cdot I(k_j = k)}_{\text{Treatment effects}} + \underbrace{\tau \cdot I(s_j = 2)}_{\text{Period time effect}}$$

Estimation of treatment effect in arm 2

Interim analysis in arm 1 at the entry time of arm 2

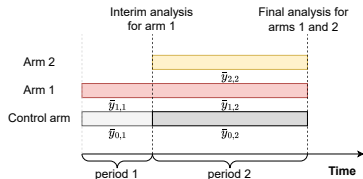
Treatment effect estimator for arm 2: $\tilde{\theta}_2 = \bar{y}_{2,2} - \tilde{y}_{0,2}$

Estimate of the control response in period 2:

If arm 1 continues at interim:

$$\tilde{y}_{0,2} = (1 - \varrho) \cdot \bar{y}_{0,2} + \varrho \cdot [\bar{y}_{0,1} + \underbrace{\bar{y}_{1,2} - \bar{y}_{1,1}}_{\text{Time trend estimate}}]$$

$$\varrho = \frac{\frac{1}{n_{0,2}}}{\frac{1}{n_{0,1}} + \frac{1}{n_{0,2}} + \frac{1}{n_{1,1}} + \frac{1}{n_{1,2}}}$$



Estimation of treatment effect in arm 2

Interim analysis in arm 1 at the entry time of arm 2

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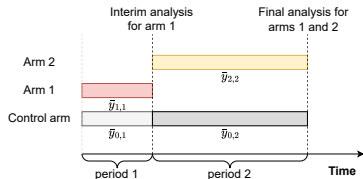
$$\tilde{y}_{0,2} = (1 - \varrho) \cdot \bar{y}_{0,2} + \varrho \cdot \underbrace{[\bar{y}_{0,1} + \bar{y}_{1,2} - \bar{y}_{1,1}]}_{\text{Time trend estimate}}$$

$$\varrho = \frac{\frac{1}{n_{0,2}}}{\frac{1}{n_{0,1}} + \frac{1}{n_{0,2}} + \frac{1}{n_{1,1}} + \frac{1}{n_{1,2}}}$$

Note: if $n_{1,2} = 0$, $\varrho = 0$

If arm 1 stops at interim:

$$\tilde{y}_{0,2} = \bar{y}_{0,2}$$



If arm 1 stops at interim, the model-based approach does **not** use non-concurrent controls.

What is the impact of the futility bound α_1 on the type I error of arm 2?

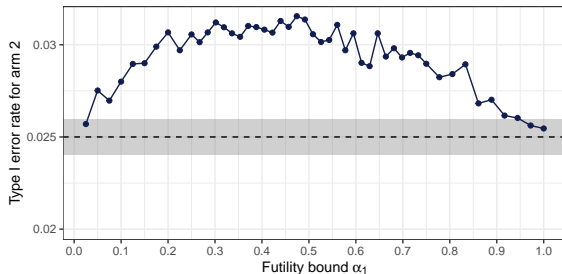
Simulation setting

- $\theta_1 = \theta_2 = 0$
- Sample sizes of 250 for arm 1 and control; and 150 for arm 2
- Varying futility bound α_1

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Type I error rate control of treatment arm 2 is lost if treatment arm 1 can be dropped at the interim analysis.

What is the impact of the effect θ_1 on the type I error of arm 2?

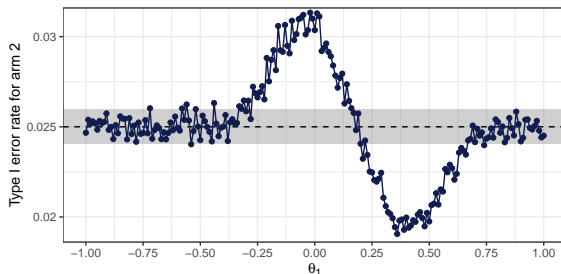
Simulation setting

- $\theta_2 = 0$
- Sample sizes of 250 for arm 1 and control; and 150 for arm 2
- Stopping for futility using futility boundary $\alpha_1 = 0.5$
- Stopping for efficacy using O'Brien-Fleming boundaries
- Varying the treatment effect θ_1 of treatment arm 1

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The **type I error rate** of treatment arm 2 is **inflated** for treatment effects of arm 1 around 0 and **deflated** in case of θ_1 around 0.4.

Key message

Including **interim analyses** to platform trials with non-concurrent controls leads to a **loss of type I error rate control** when using the regression model.

Next steps

- Evaluate the **maximum type I error rate inflation** in platform trial designs with interim analyses
- Propose **adjusted estimators** allowing for inclusion of NCC data, which either **eliminate** bias or **reduce** the bias
- Derive the **variance** of such estimators for conducting statistical tests

Selected references

- Bofill Roig, M., Krotka, P., Burman, C. F., Glimm, E., Gold, S. M., Hees, K., Jacko P., Koenig F., Magirr D., Mesenbrink P., Viele K., Posch, M., “*On model-based time trend adjustments in platform trials with non-concurrent controls.*” BMC Medical research methodology 22.1 (2022): 1-16
- Krotka, P., Hees, K., Jacko, P., Magirr, D., Posch, M., Bofill Roig, M., “*NCC: An R-package for analysis and simulation of platform trials with non-concurrent controls.*” SoftwareX 23 (2023): 101437.
- Krotka, P., Posch, M., Gewily, M., Höglinger, G., Bofill Roig, M., “*Statistical modeling to adjust for time trends in adaptive platform trials utilizing non-concurrent controls.*” arXiv preprint arXiv:2403.14348 (2024).
- Lee, K. M., and Wason, J. “*Including non-concurrent control patients in the analysis of platform trials: is it worth it?*” BMC Medical research methodology 20.1 (2020): 1-12.
- Saville, B. R., Berry, D. A., Berry, N. S., Viele, K., Berry, S. M., et al. “*The Bayesian Time Machine: Accounting for Temporal Drift in Multi-arm Platform Trials.*” Clinical Trials 19.5 (2022): 490-501
- Woodcock, J., and LaVange, L. M. *Master Protocols to Study Multiple Therapies, Multiple Diseases, or Both.* New England Journal of Medicine 377.1 (2017): 62–70

Thank you for your attention!



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