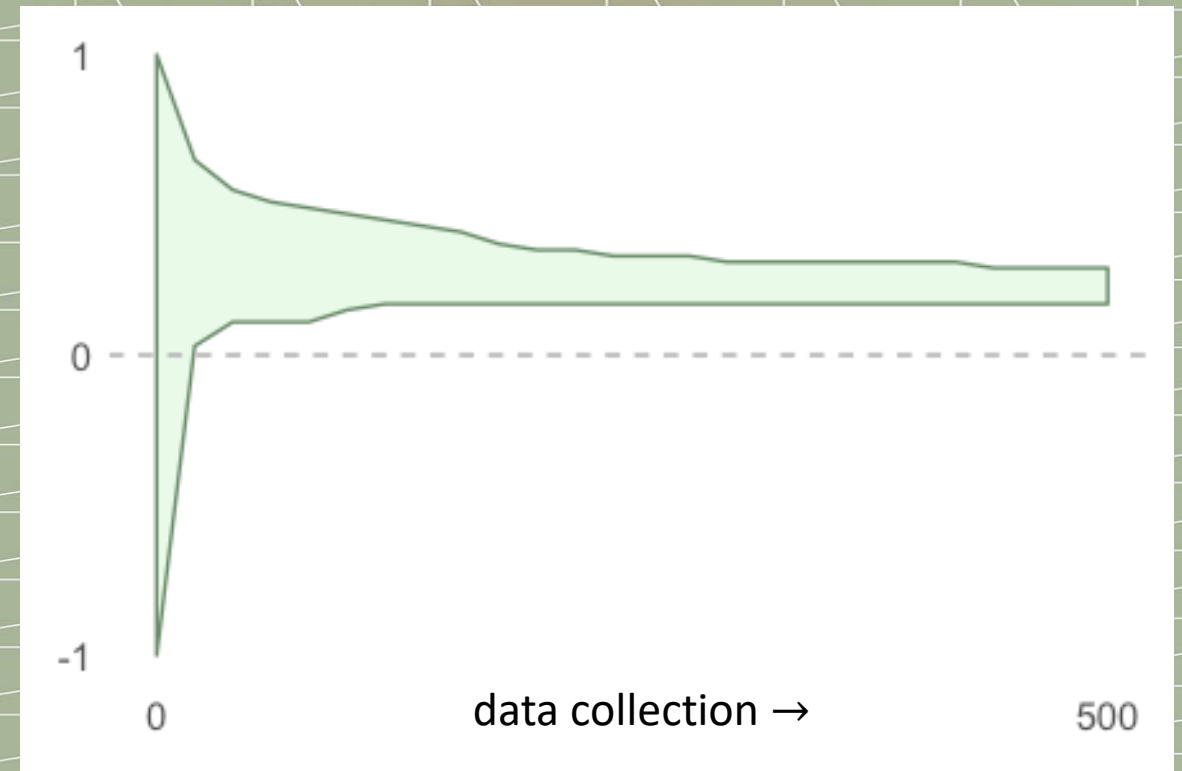


Anytime-valid testing and confidence intervals in contingency tables and beyond

Rosanne J. Turner and Peter Grünwald

A/B Testing Workshop 2022

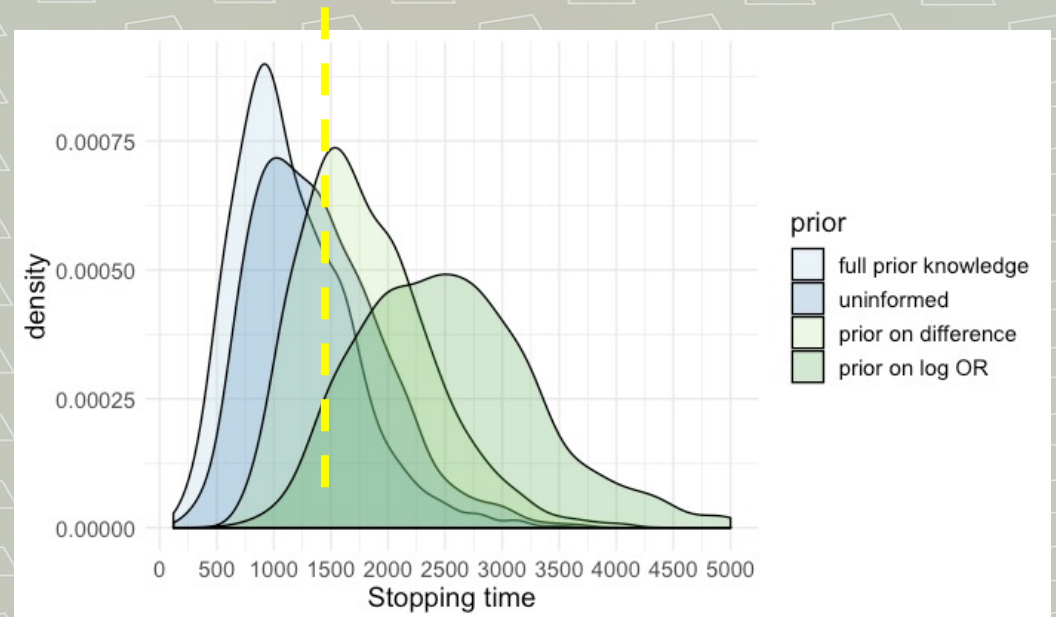
Goal: tests that can be used under optional stopping (sequential research), *with a notion of effect size*



Example: SWEPIIS study on stillbirth

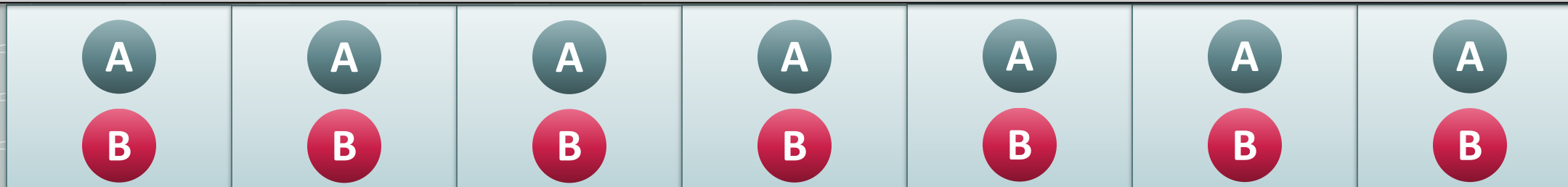
- Comparing perinatal death in labour induction at 41 or 42 weeks
- Stopped after ± 1380 births in each group: 6 perinatal deaths in 42 weeks group
- ***Sequential test*** with balanced design: ***would often have stopped earlier***

Simulated stopping times with and without using knowledge from previous studies in sequential test*



* SWEPIIS study: Wennerholm et al. published in *bmj*, 367, 2019. Figure: adapted from Turner et al., 2021

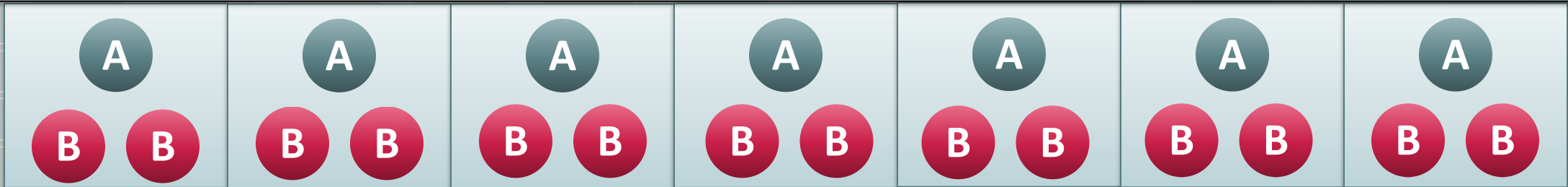
Flexible, sequential setting



- data come in a stream of data blocks $j = 1, 2, \dots$
- each block has $n = n_a + n_b$ observations
- observations seen up to and including block j :

$$y_a^{(j)} = (y_{1,a}, \dots, y_{j n_a, a}) \text{ and } y_b^{(j)} = (y_{1,b}, \dots, y_{j n_b, b})$$

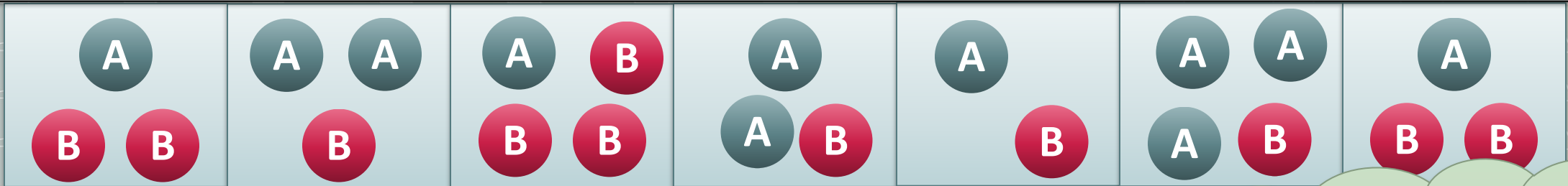
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O.K. as long as we "lock in" block composition before start of that block!

Running example: 2x2 contingency table setting

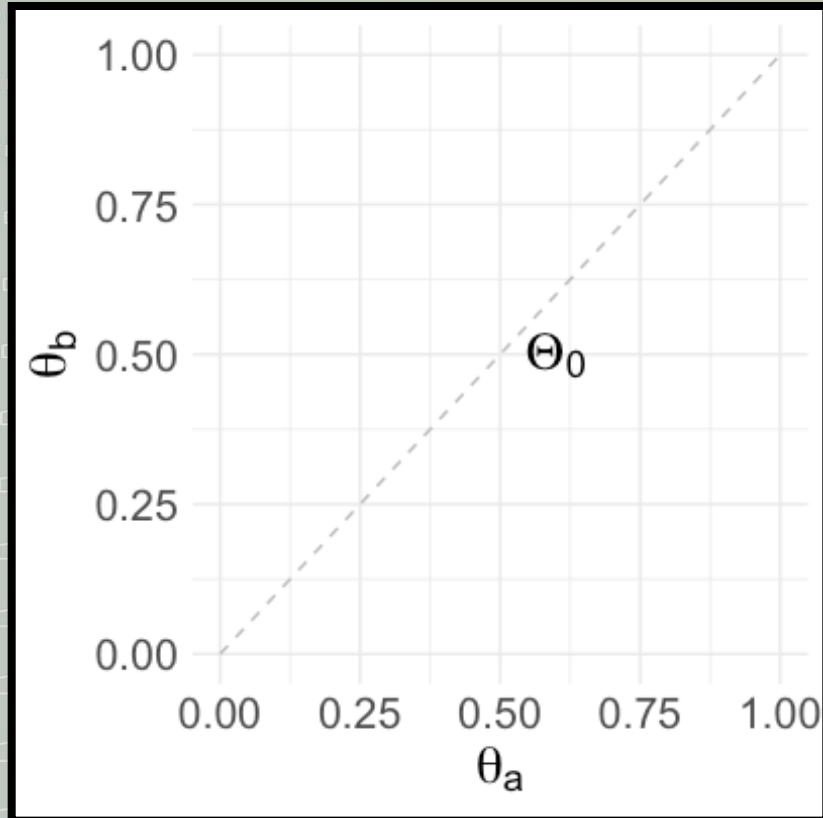
2x2 contingency table

		Strategy	
		A	B
Outcome	Success	S(A)	S(B)
	Failure	F(A)	F(B)

Do success probabilities differ between strategies?

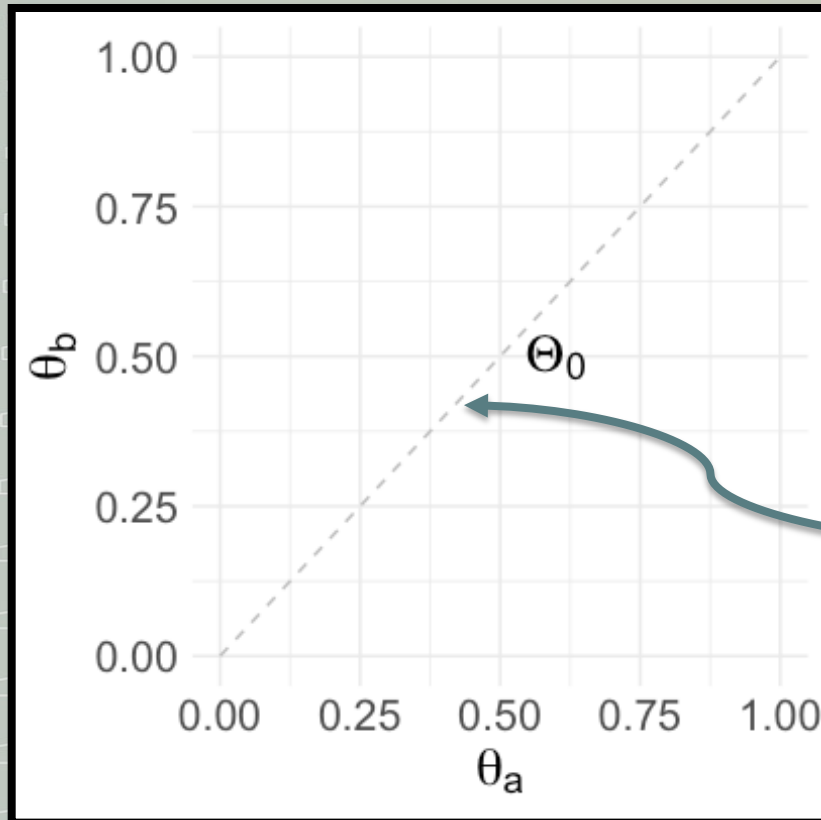
- \mathcal{H}_0 : observations $Y \in \{0,1\}$ independent of strategy $X \in \{a, b\}$
- Equivalently, when $Y_x \stackrel{i.i.d.}{\sim} \text{Bernoulli}(\theta_x)$:
 $\mathcal{H}_0: \theta_a = \theta_b$.

2x2 contingency table setting



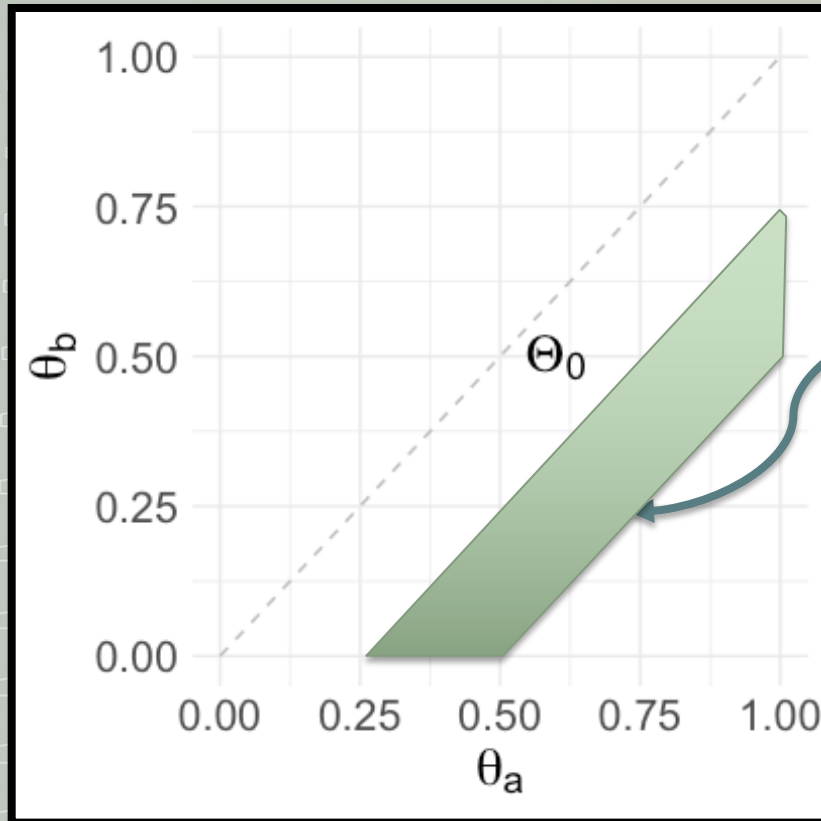
“True” success probabilities
for each strategy somewhere
in the unit square

2x2 contingency table setting



Testing: outside of the dashed line?

2x2 contingency table setting

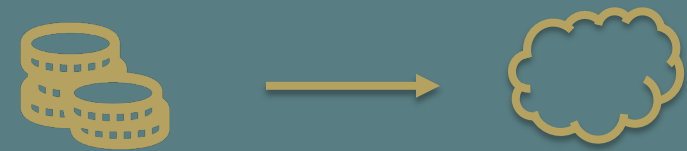


Estimating: somewhere in the shaded area?

Tool for analyzing sequential data: E-variables*

- Nonnegative RV S , where for all $P_0 \in \mathcal{H}_0$:
$$\mathbb{E}_{P_0}[S] \leq 1$$
- Straightforward implementation in test: reject \mathcal{H}_0 iff $S \geq \alpha^{-1}$
- Type-I error guarantee at α (e.g. $\alpha = 0.05$, reject if $S \geq 20$)

Betting interpretation
 \mathcal{H}_0 true? Expect no profit



High profit? Reject \mathcal{H}_0



Point alternative 2 data streams: nice general expression!

Point \mathcal{H}_1 P_{θ_a, θ_b} (Turner, 2021):

$$S(Y^{(1)}) := \prod_{i=1}^{n_a} \frac{p_{\theta_a}(Y_{i,a})}{p_{\theta_0}(Y_{i,a})} \prod_{i=1}^{n_b} \frac{p_{\theta_b}(Y_{i,b})}{p_{\theta_0}(Y_{i,b})}$$

E-variable when we choose $\theta_0 = (n_a/n)\theta_a + (n_b/n)\theta_b$

E-process for two data streams

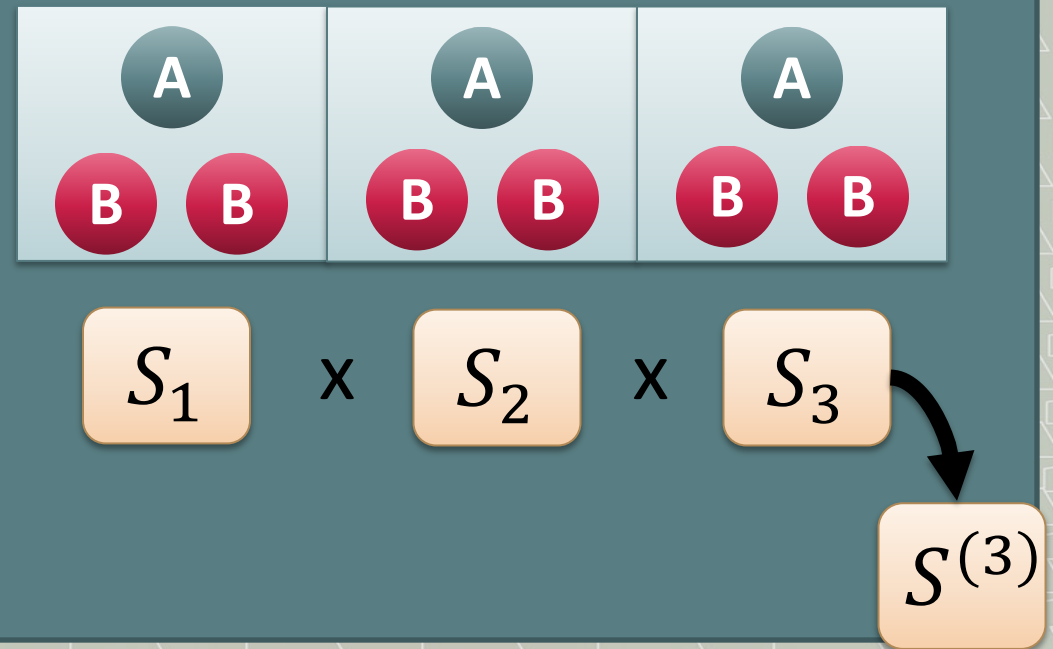
- Can make an **e-process**: multiply E-values for all data blocks

$$S^{(m)}(Y^{(m)}) := \prod_{j=1}^m S(Y_j)$$

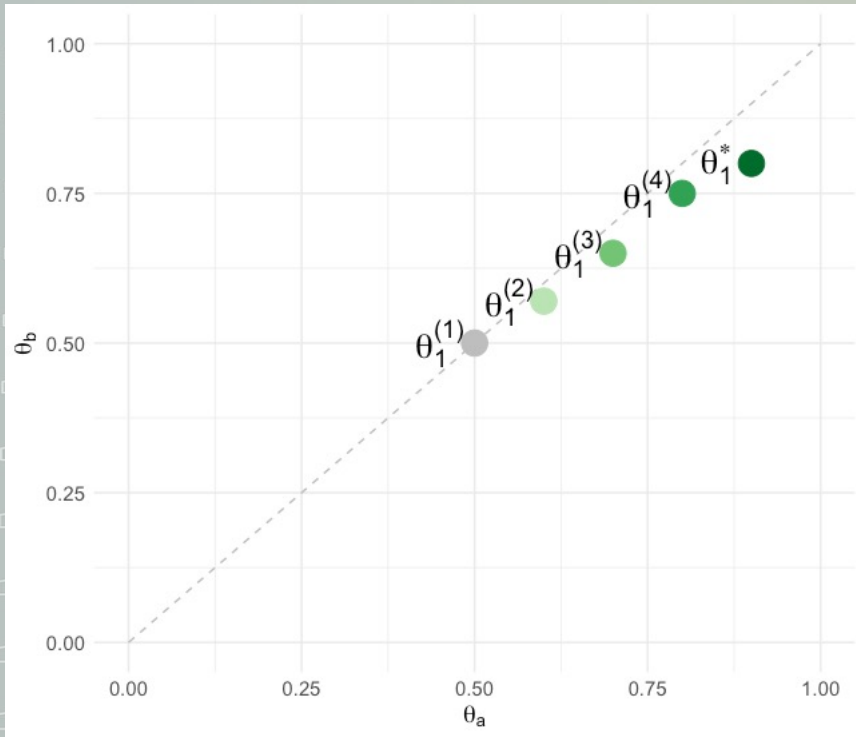
- For **arbitrary stopping rule** (E-value ≥ 20 , no money for further experiment, etc.):

$$P_0(\exists m: S^{(m)}(Y^{(m)}) \geq \alpha^{-1}) \leq \alpha$$

Key: multiplying E-values yields another E-value

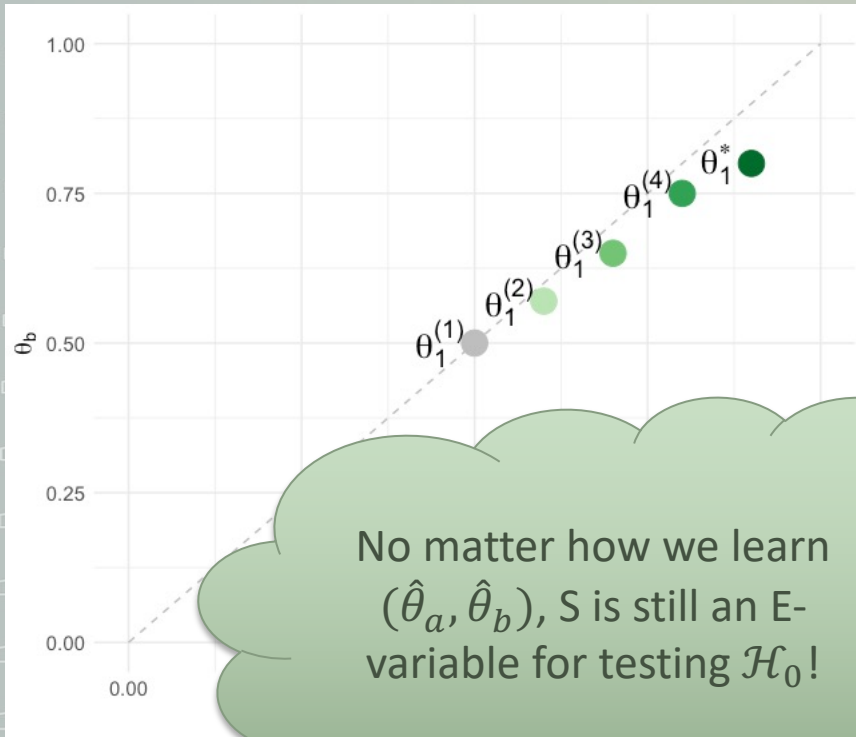


Learn parameter for \mathcal{H}_1



- Can learn estimate $(\hat{\theta}_a, \hat{\theta}_b)$ of true alternative before each new data block, based on past data
 - Maximum likelihood
 - MAP estimator
 - Posterior mean, ...
- Restrict search space based on expert knowledge

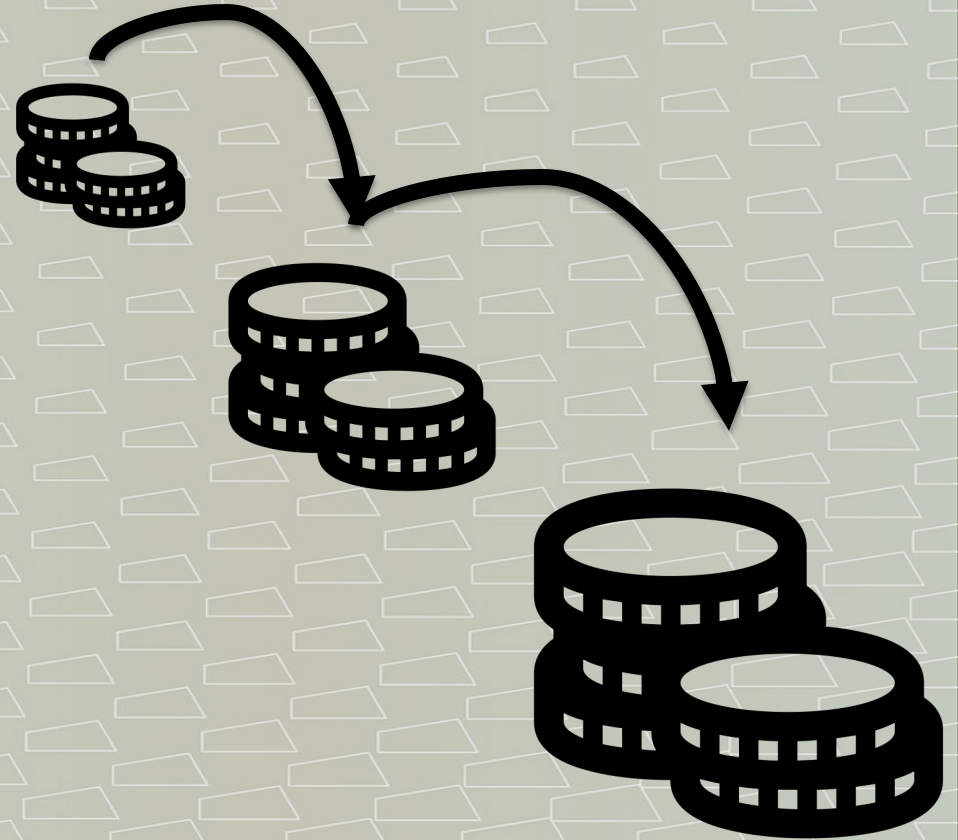
Learn parameter for \mathcal{H}_1



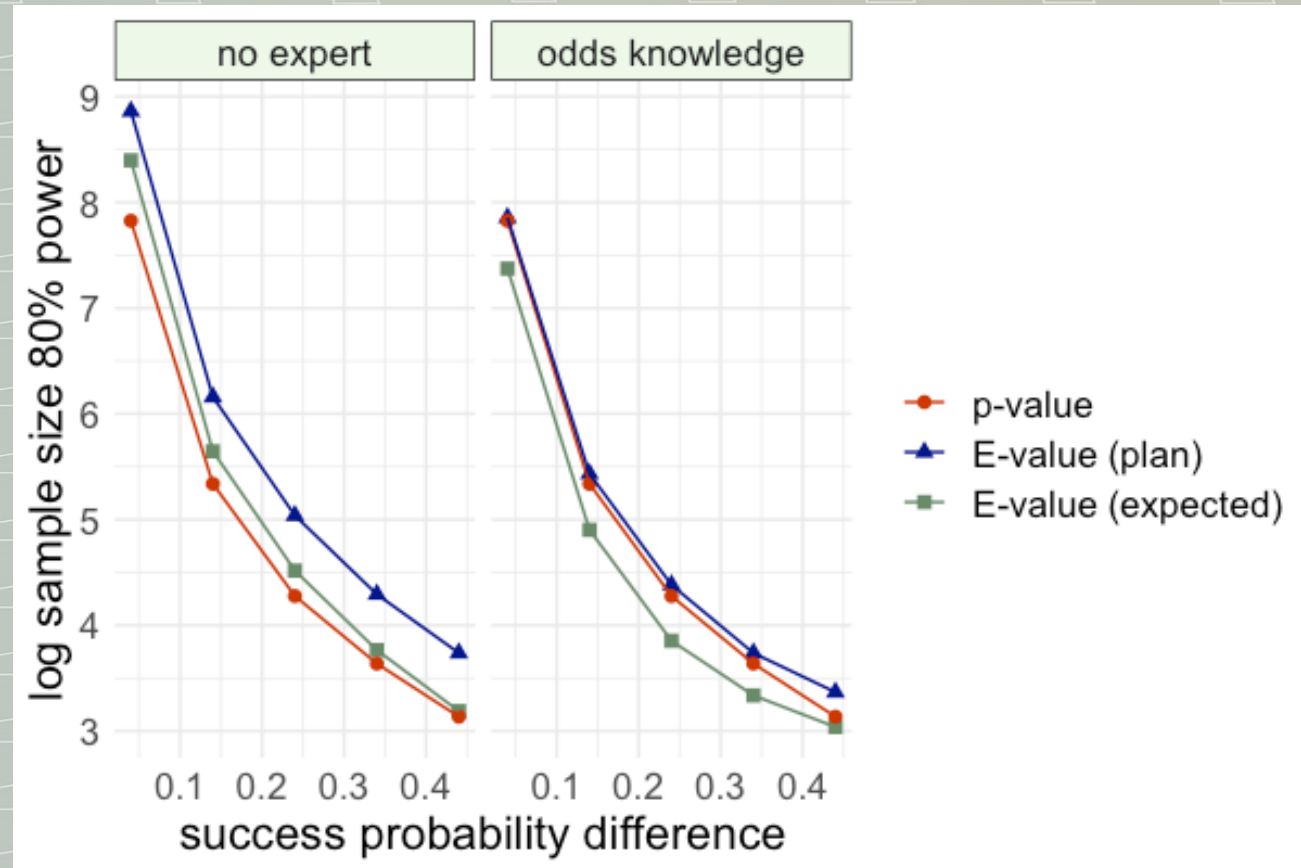
- Can learn estimate $(\hat{\theta}_a, \hat{\theta}_b)$ of true alternative before each new data block, based on past data
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Evidence against \mathcal{H}_1 and Type-II error

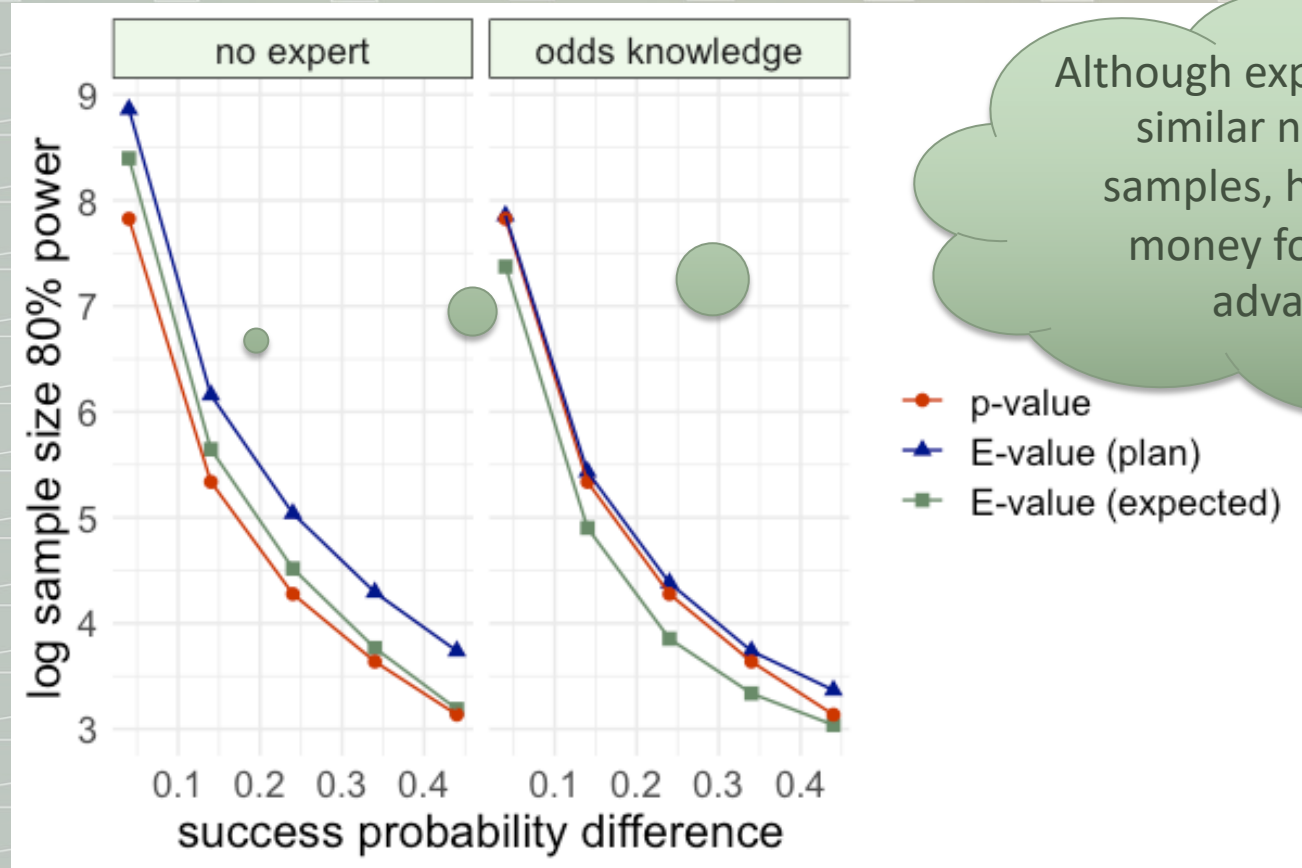
- **GRO criterion:** in sequential experiments: optimize “growth rate” of E-variable, $\mathbb{E}_{P_1}[\log S]$ (Grünwald, 2019)
- Minimize notion of **regret:** loss of capital growth under alternative due to not knowing true P_1 .
- Closely connected to optimizing power



2x2 E-values vs classical counterpart



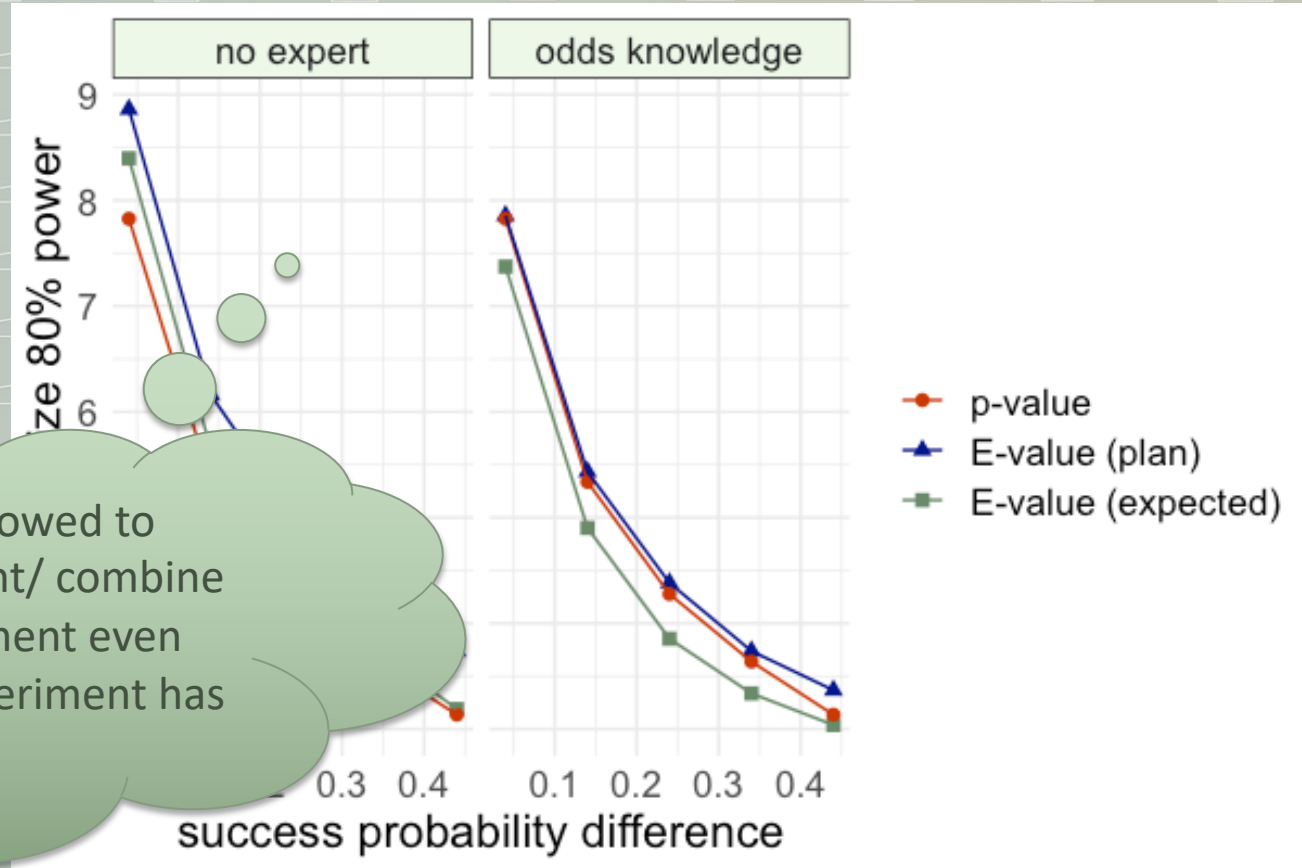
2x2 E-values vs classical counterpart



Although expect to collect similar number of samples, have to allot money for more in advance...

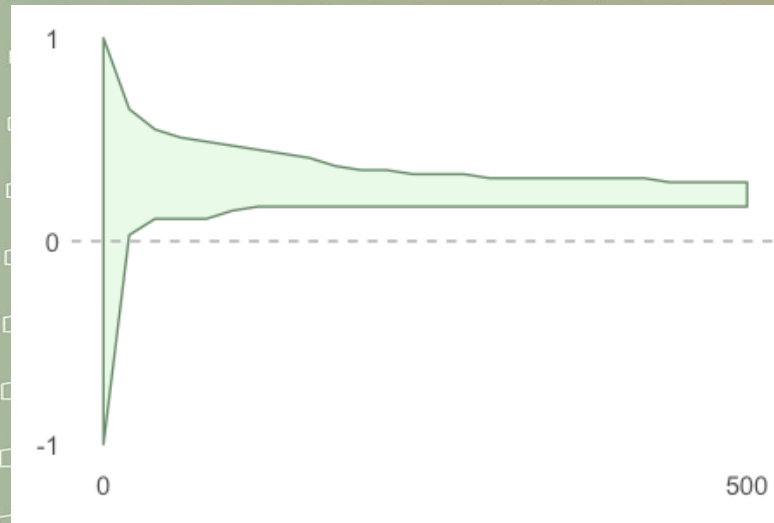
Figure adapted from Turner et al., 2021, figure 4

2x2 E-values vs classical counterpart



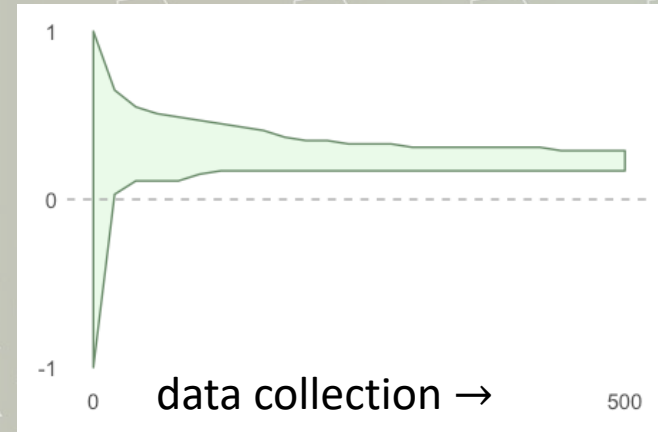
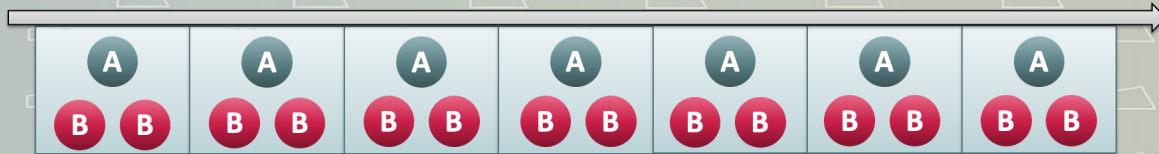
On plus side: allowed to continue experiment/ combine with new experiment even years after first experiment has ended!

Extension to confidence intervals



Anytime-valid confidence sequences

Update effect size estimate each time a new batch of data has come in, **with coverage guarantee** (real value is in my estimate with some minimum probability)



Formally; confidence sequence CS with coverage at level $(1 - \alpha)$:

- $P_{\theta_a, \theta_b} \left(\text{for any } m = 1, 2, \dots : \delta(\theta_a, \theta_b) \notin CS_{(m)} \right) \leq \alpha$
- $\delta(\theta_a, \theta_b)$: measure of *effect size*

Key: use E-process to test effect size values

- Let $S_{\Theta_0(\delta)}^{(m)}$ be an E-process for testing:
 $\mathcal{H}_0 := \{P_{\theta_0} : \theta_0 \in \Theta_0(\delta)\}$
- Probability of falsely rejecting \mathcal{H}_0 bounded by α (because it is an E-process)!
- Construct anytime-valid confidence sequence $CS_{\alpha,(m)} = \left\{ \delta : S_{\Theta_0(\delta)}^{(m)} \leq \frac{1}{\alpha} \right\}$
- \rightarrow gives us the desired coverage at level $(1 - \alpha)$.

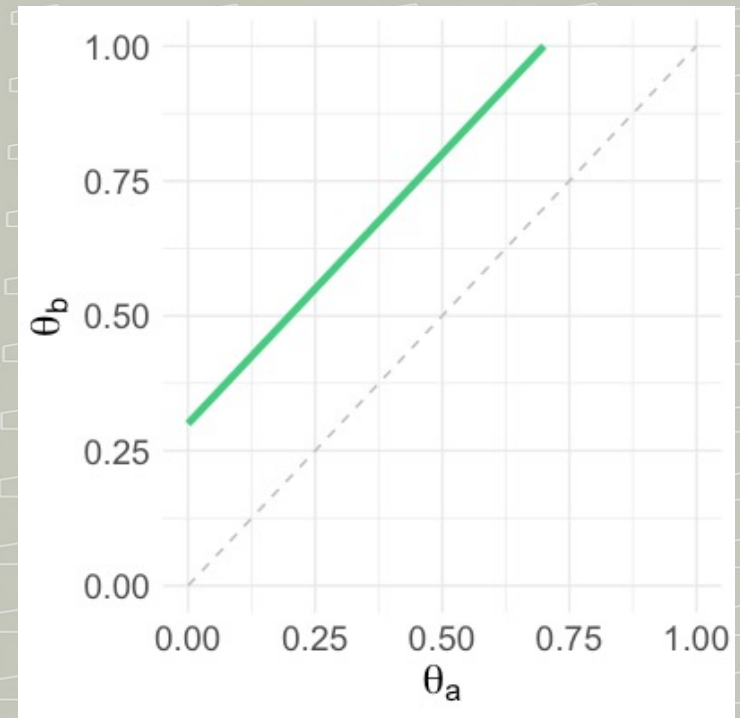
Extension to \mathcal{H}_0 beyond $\theta_a = \theta_b$: examples

Effect size $\delta: (\theta_a, \theta_b) \rightarrow \gamma; \gamma \in \Gamma$.

– E.g. Risk Difference: $\delta(\theta_a, \theta_b) = \theta_b - \theta_a, \Gamma = [-1, 1]$

– E.g. Odds Ratio: $\delta(\theta_a, \theta_b) = \frac{\theta_b}{1-\theta_b} \frac{1-\theta_a}{\theta_a}, \Gamma = \mathbb{R}^+$

$$\Theta_0(\delta) = \{(\theta_a, \theta_b): \theta_b - \theta_a = 0.3\}$$



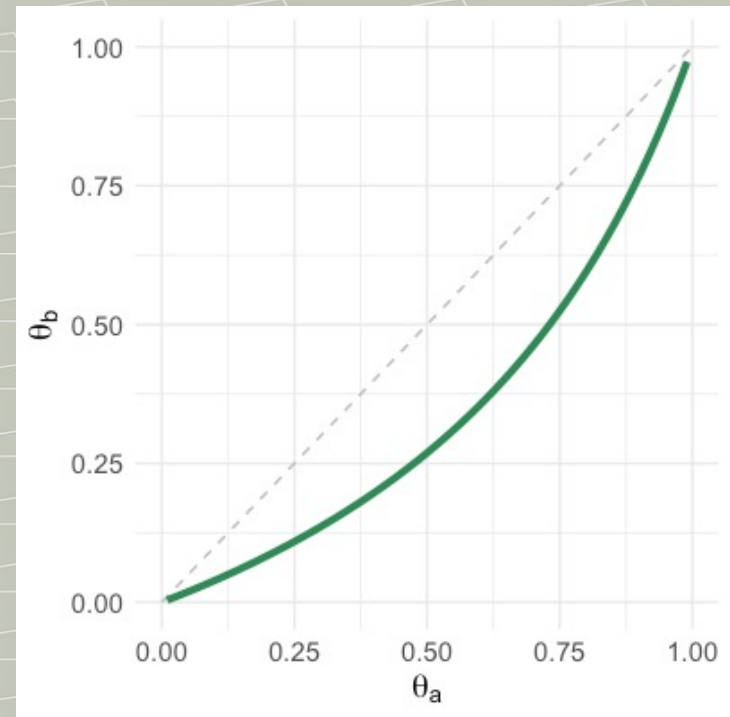
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$$\Theta_0(\delta) = \{(\theta_a, \theta_b): lOR(\theta_b, \theta_a) = -1\}$$



Extension of E-variable for streams to general null hypothesis $\Theta_0(\delta)$ for 2x2 tables

$$S_{\Theta_0}(Y^{(1)}) := \prod_{i=1}^{n_a} \frac{p_{\hat{\theta}_a}(Y_{i,a})}{p_{\theta_a^\circ}(Y_{i,a})} \prod_{i=1}^{n_b} \frac{p_{\hat{\theta}_b}(Y_{i,b})}{p_{\theta_b^\circ}(Y_{i,b})},$$

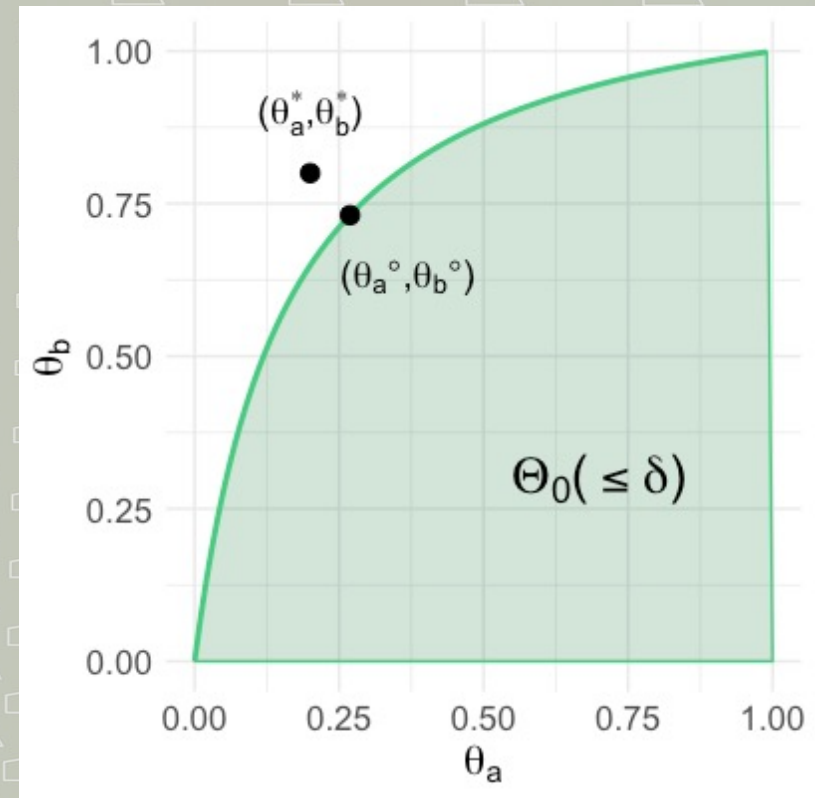
where $(\theta_a^\circ, \theta_b^\circ)$ achieve

$$\min_{(\theta_a, \theta_b) \in \Theta_0(\delta)} D(P_{\hat{\theta}_a, \hat{\theta}_b}(Y_a^{n_a}, Y_b^{n_b}) | P_{\theta_a^\circ, \theta_b^\circ}(Y_a^{n_a}, Y_b^{n_b}))$$

and we estimate the point $(\hat{\theta}_a, \hat{\theta}_b)$ as before (Turner, 2022)

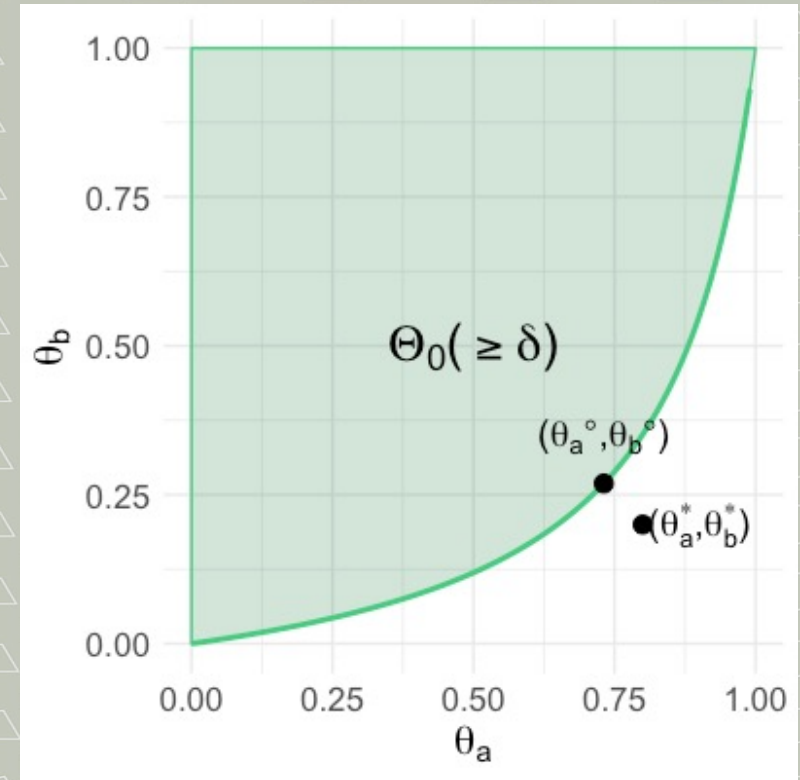
Tricky case: odds ratio and convexity of \mathcal{H}_0

- Need convexity of $\Theta_0(\delta)$ to construct E-variable
- $\delta > 0 \rightarrow$ can estimate lower bound (see figure)
- $\delta < 0 \rightarrow$ can estimate upper bound

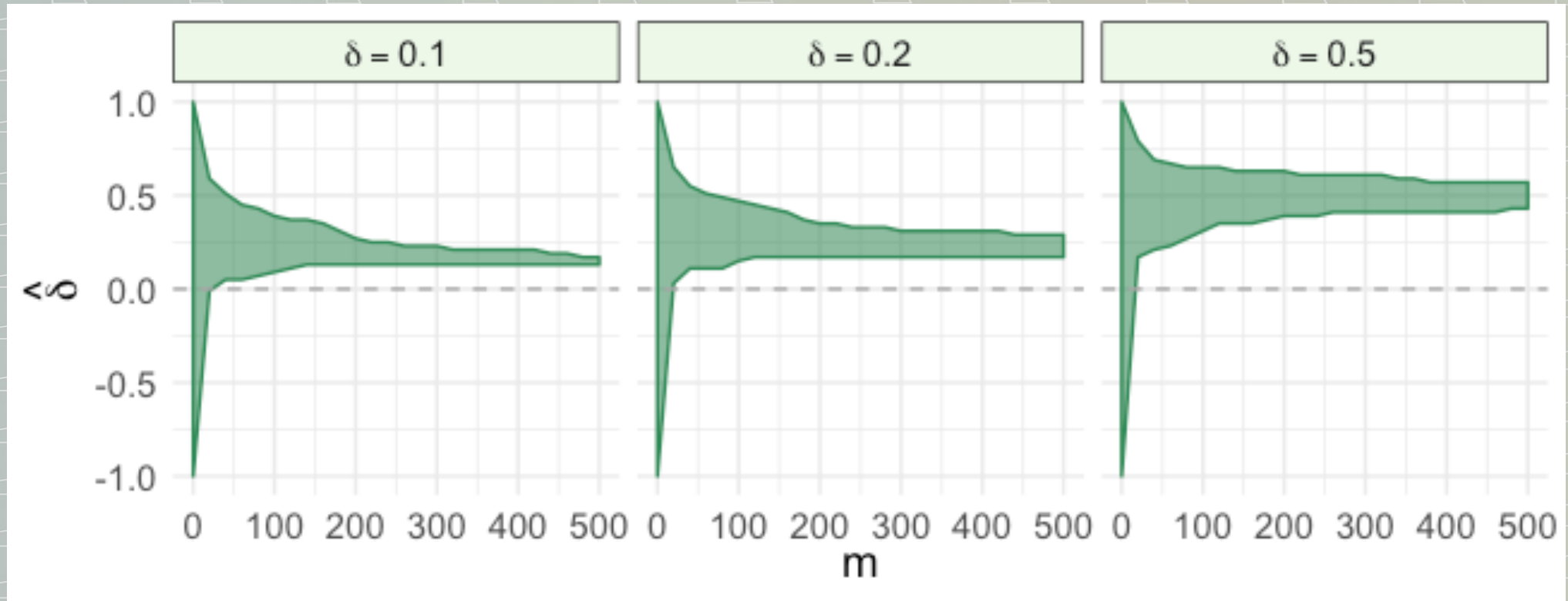


Tricky case: odds ratio and convexity of \mathcal{H}_0

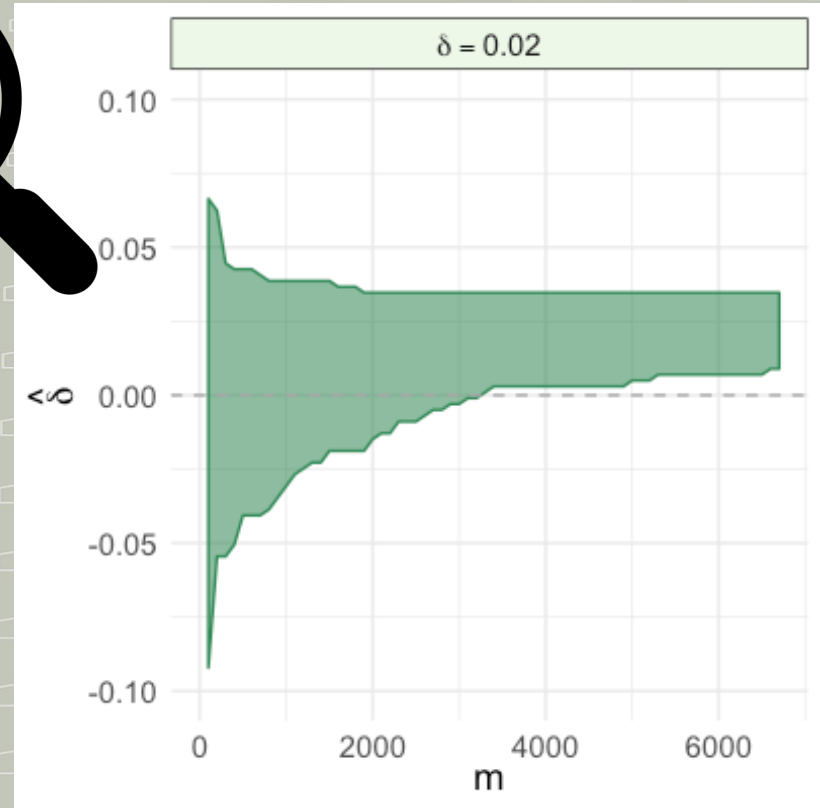
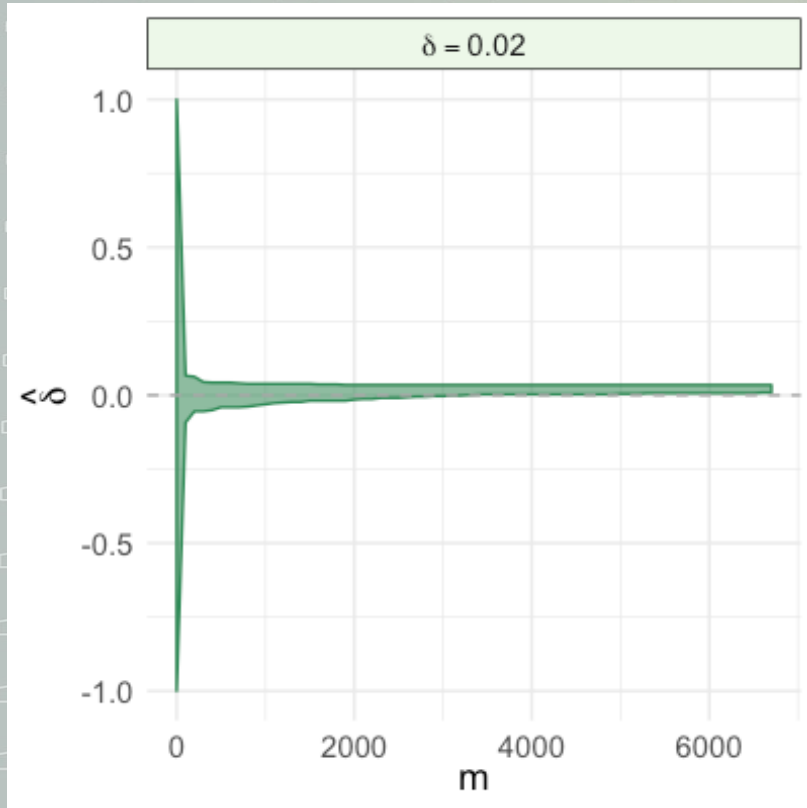
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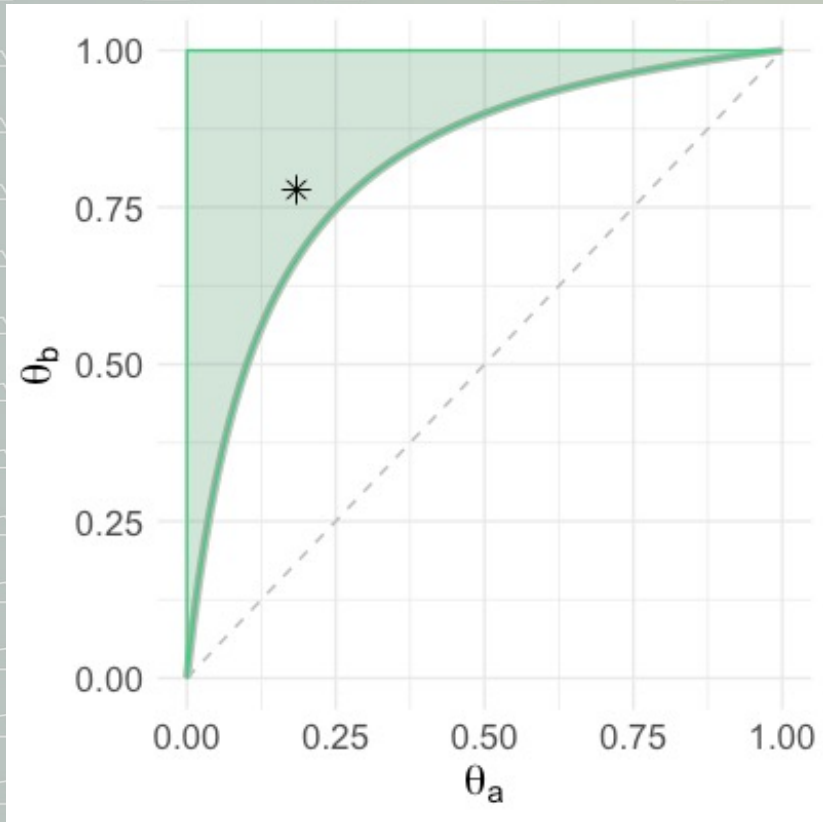
Simulations: risk difference



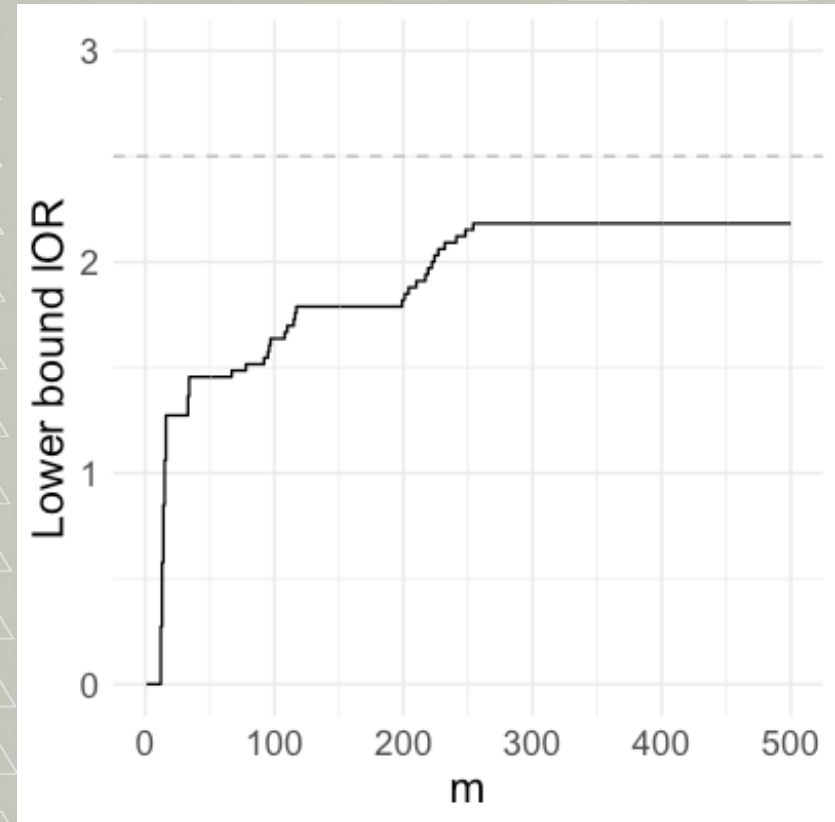
Simulations: risk difference



Simulation: log of the odds ratio

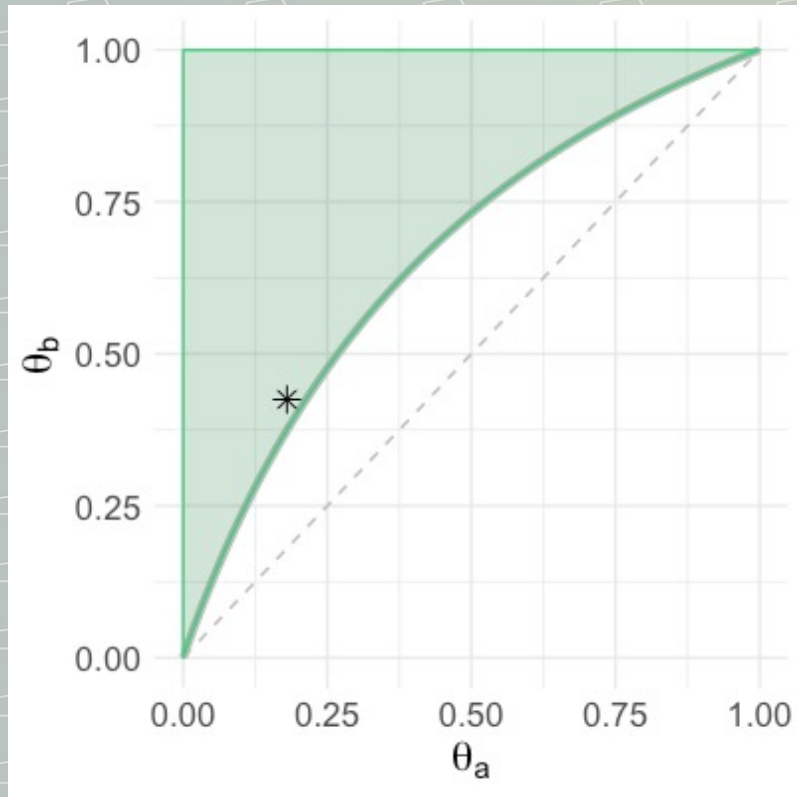


One-sided CS^+ at data block $m = 500$

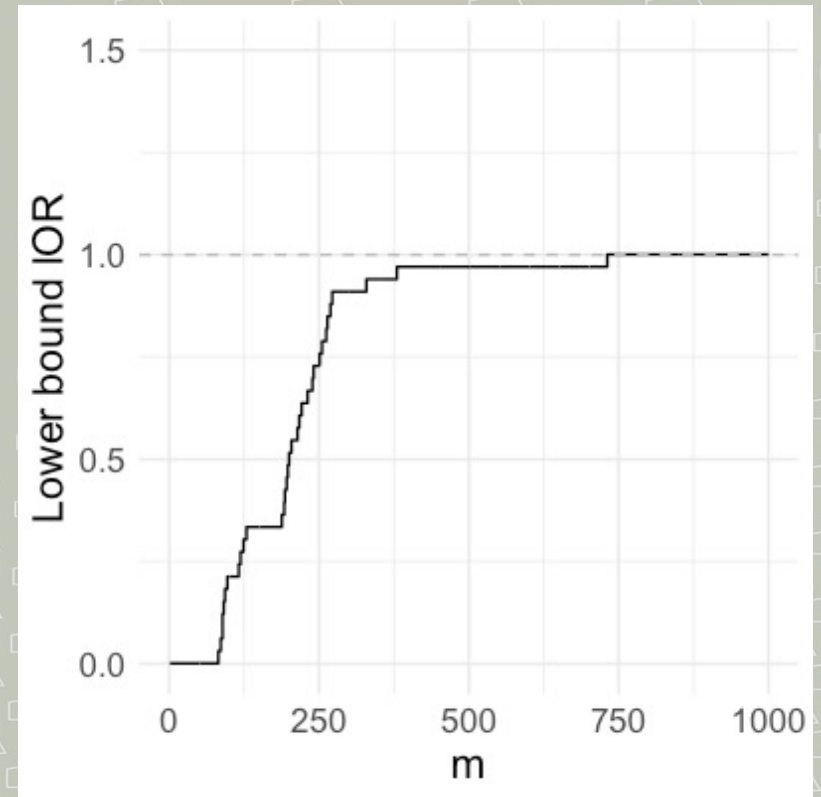


lower bound over time

Simulation: log of the odds ratio



One-sided CS^+ at data block $m = 500$



lower bound over time

Conclusion and novelty

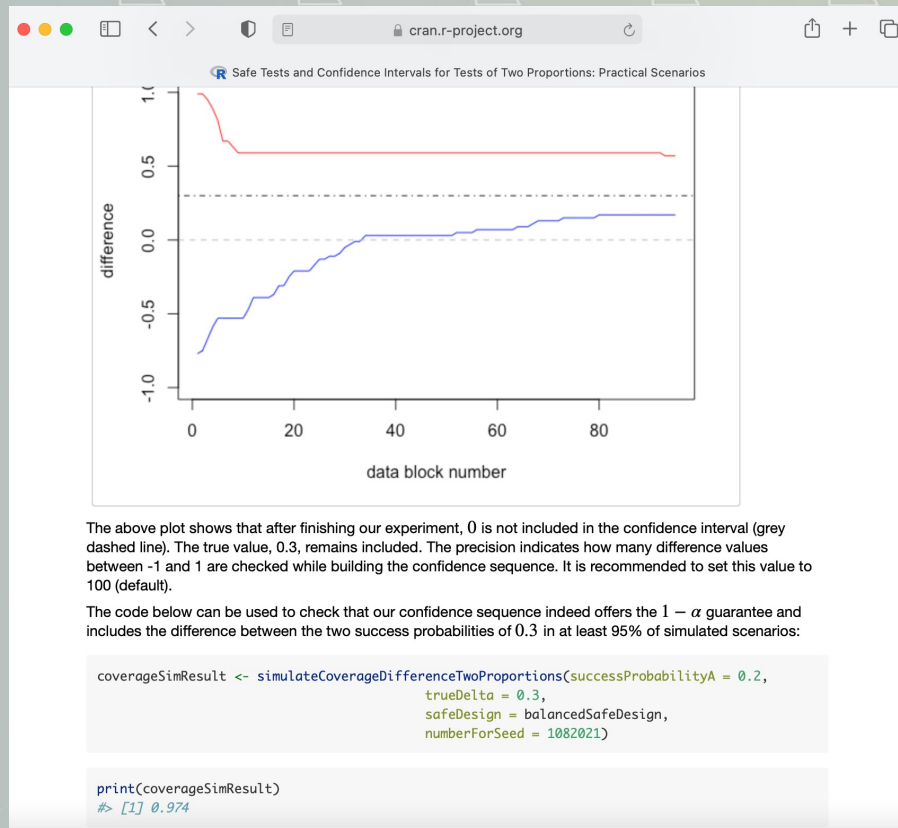
- To our knowledge, really new:
 - **flexibility** (block size, user-specified notions of effect size)
 - **growth rate optimality**: expect evidence for H1 to **grow as fast as possible** during data collection
- Wald's sequential probability ratio test:
 - Probability ratios can be interpreted as “alternative” E-variables
 - Not growth-rate optimal
 - Only allow for testing odds ratio effect size

Extensions

- Beyond Bernoulli: GRO property? (work by Y. Hao and others)
- Stratified data and conditional independence
 - Use case at UMC Utrecht: real-time psychiatry research and recommendations

		Strategy	
		A	B
Stratum 1	Success	S(A1)	S(B1)
	Failure	F(A1)	F(B1)
Stratum 2	Success	S(A2)	S(B2)
	Failure	F(A2)	F(B2)
Stratum 3	Success	S(A3)	S(B3)
	Failure	F(A3)	F(B3)

R Package and Vignettes



- In R console:
`install.packages("safestats")`
- <https://CRAN.R-project.org/package=safestats>

Further reading and references

- On the theory of E-values:
 - P.D. Grünwald, R. de Heide and W. Koolen (2019) on ArXiv:
 - V. Vovk and R. Wang (2021). E-values: Calibration, combination, and applications. *Annals of Statistics*.
 - G. Shafer (2021). Testing by betting: A strategy for statistical and scientific communication. *Journal of the Royal Statistical Society, Series A*.
- On implementations of E-values:
 - R.J. Turner, A. Ly and P.D. Grünwald (2021) on ArXiv:2106.02693
 - R.J. Turner and P.D. Grünwald (2022) on ArXiv:2203.09785
 - R software: <https://CRAN.R-project.org/package=safestats>