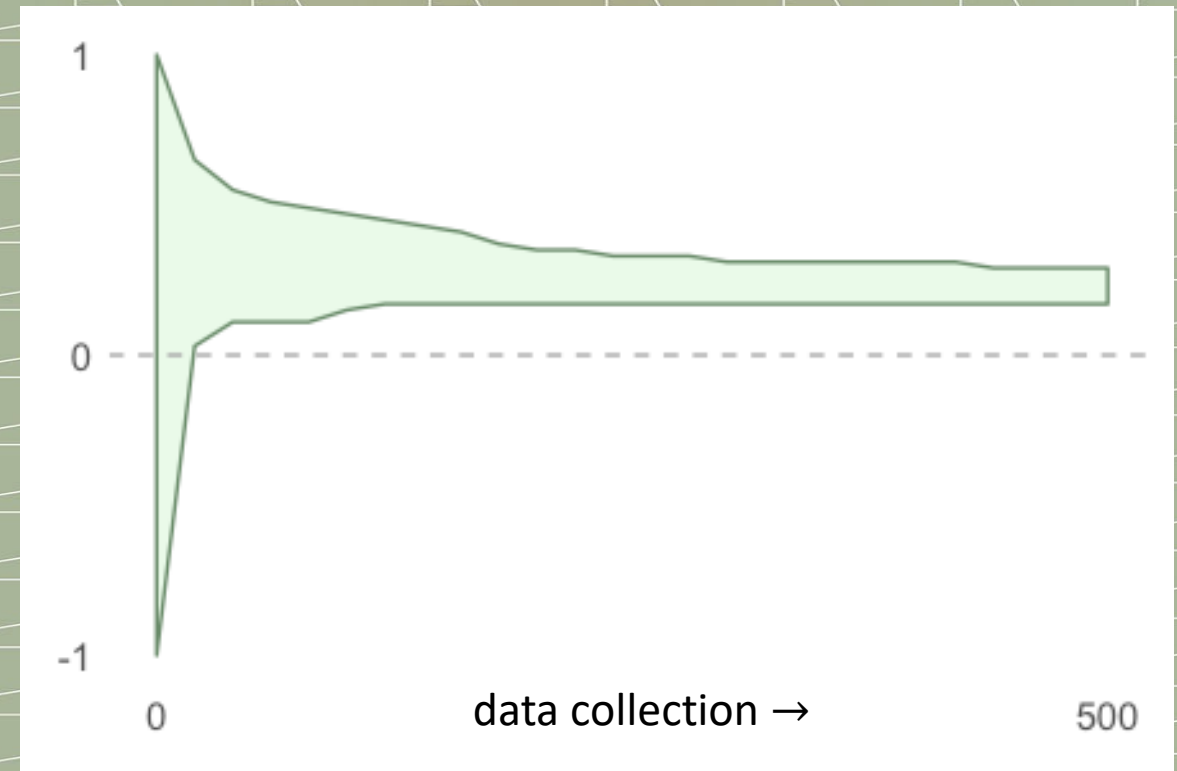


# Anytime-valid testing and confidence intervals in contingency tables and beyond

Rosanne J. Turner and Peter Grünwald

A/B Testing Workshop 2022

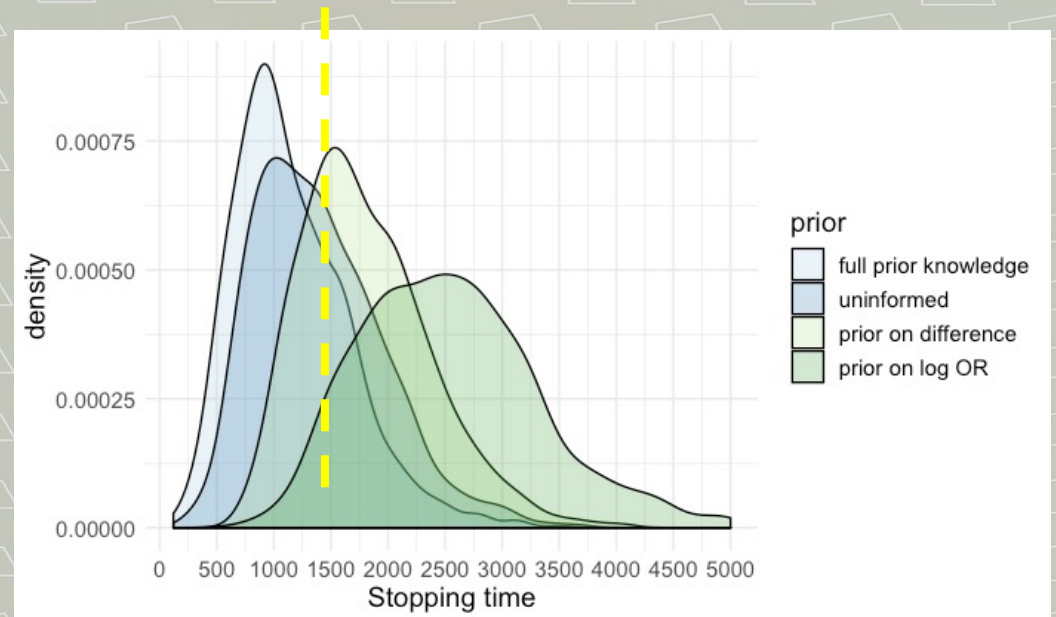
Goal: tests that can be used under optional stopping (sequential research), *with a notion of effect size*



# Example: SWEPIIS study on stillbirth

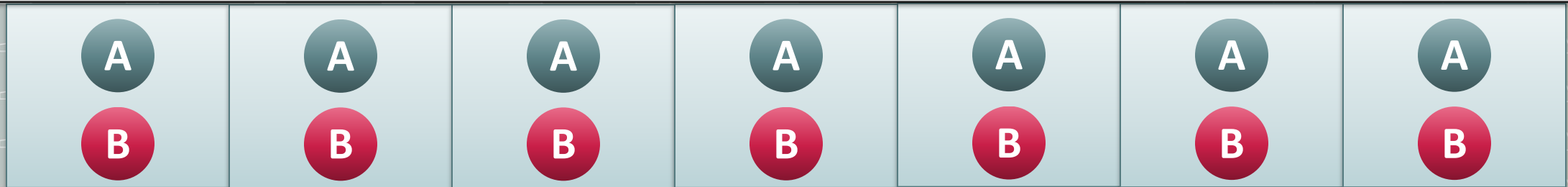
- Comparing perinatal death in labour induction at 41 or 42 weeks
- Stopped after  $\pm 1380$  births in each group: 6 perinatal deaths in 42 weeks group
- ***Sequential test*** with balanced design: ***would often have stopped earlier***

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

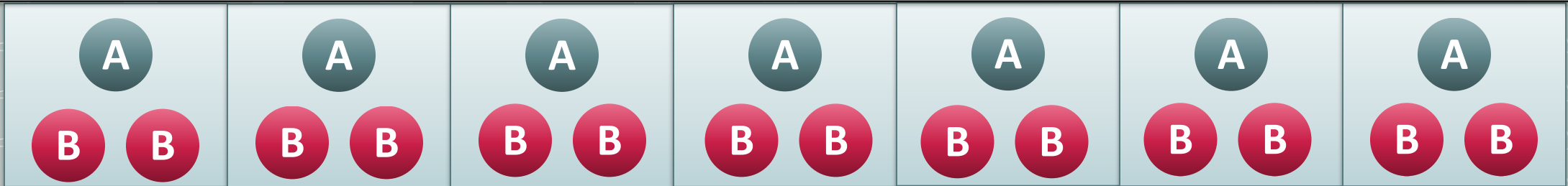
# Flexible, sequential setting



- 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  $j$ :

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

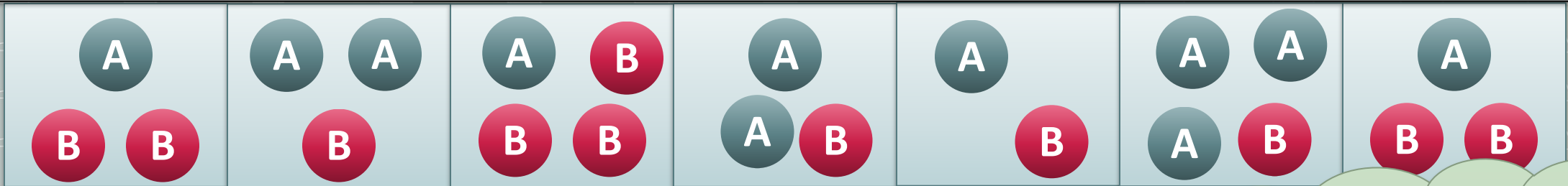
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O.K. as long as we "lock in" block composition before start of that block!

# Running example: 2x2 contingency table setting

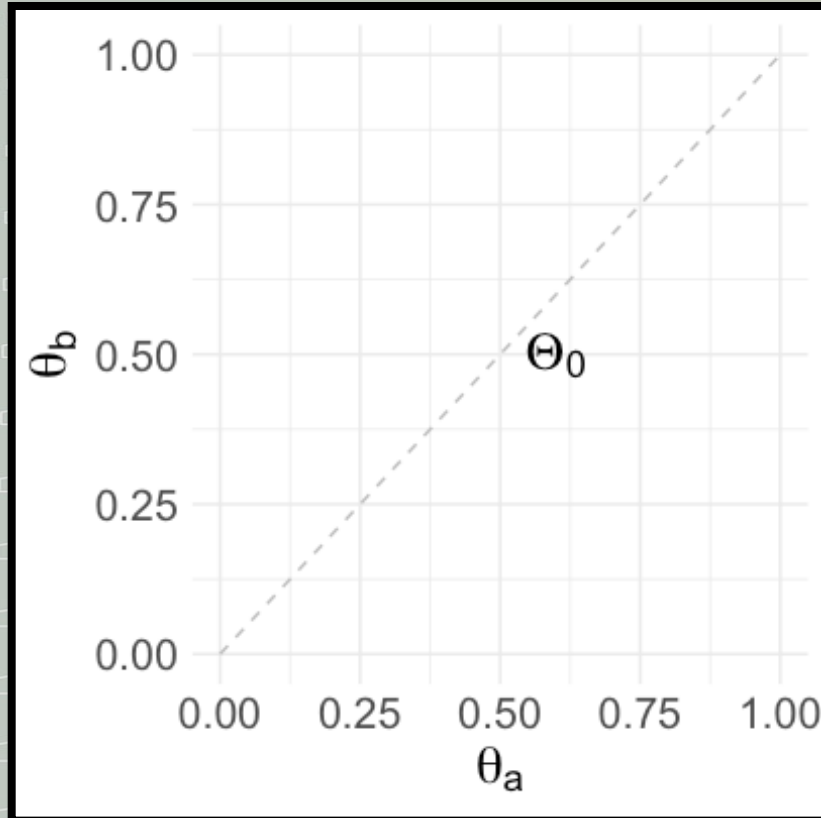
2x2 contingency table

		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  $Y_x \stackrel{i.i.d.}{\sim} \text{Bernoulli}(\theta_x)$ :  
 $\mathcal{H}_0: \theta_a = \theta_b$ .

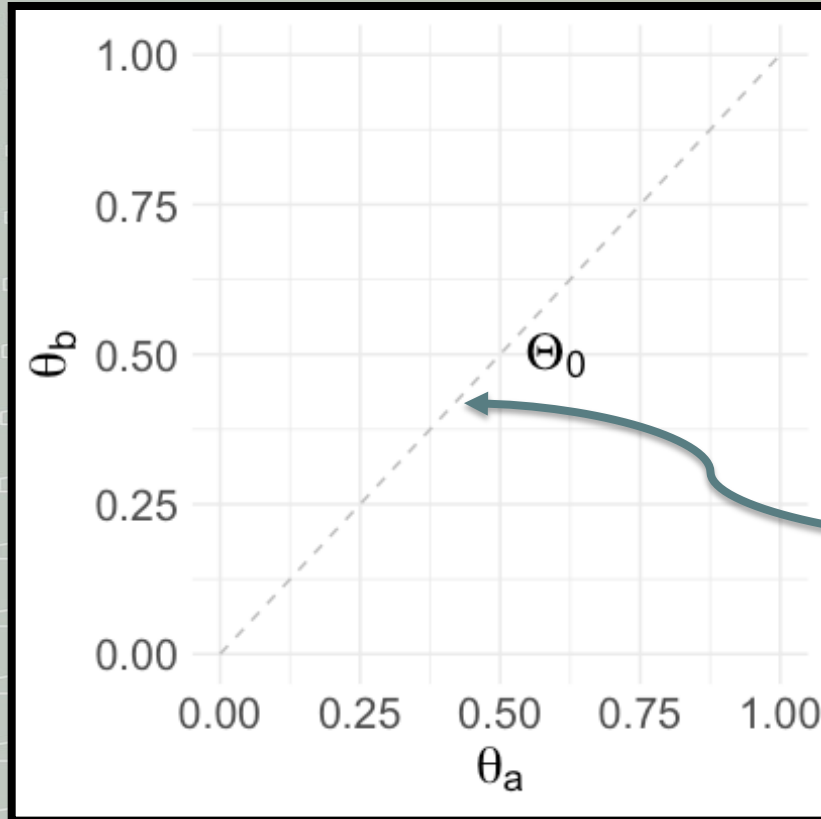
# 2x2 contingency table setting



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

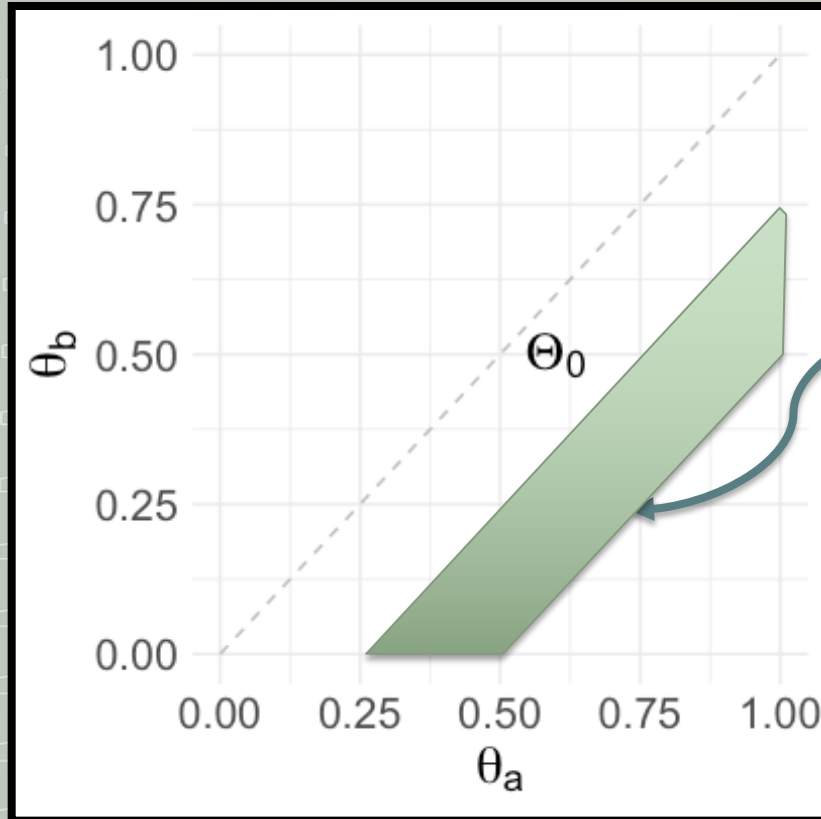


# 2x2 contingency table setting



Testing: outside of the dashed line?

# 2x2 contingency table setting



Estimating: somewhere in the shaded area?

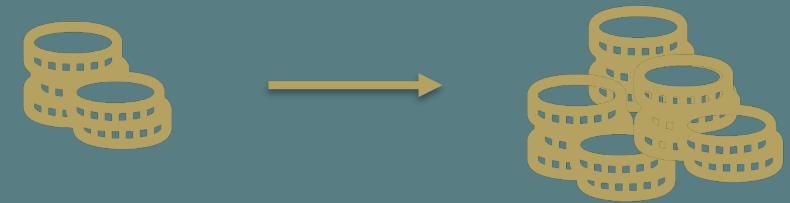
# Tool for analyzing sequential data: E-variables\*

- 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  $\alpha$  (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  $\mathcal{H}_1$   $P_{\theta_a, \theta_b}$  (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

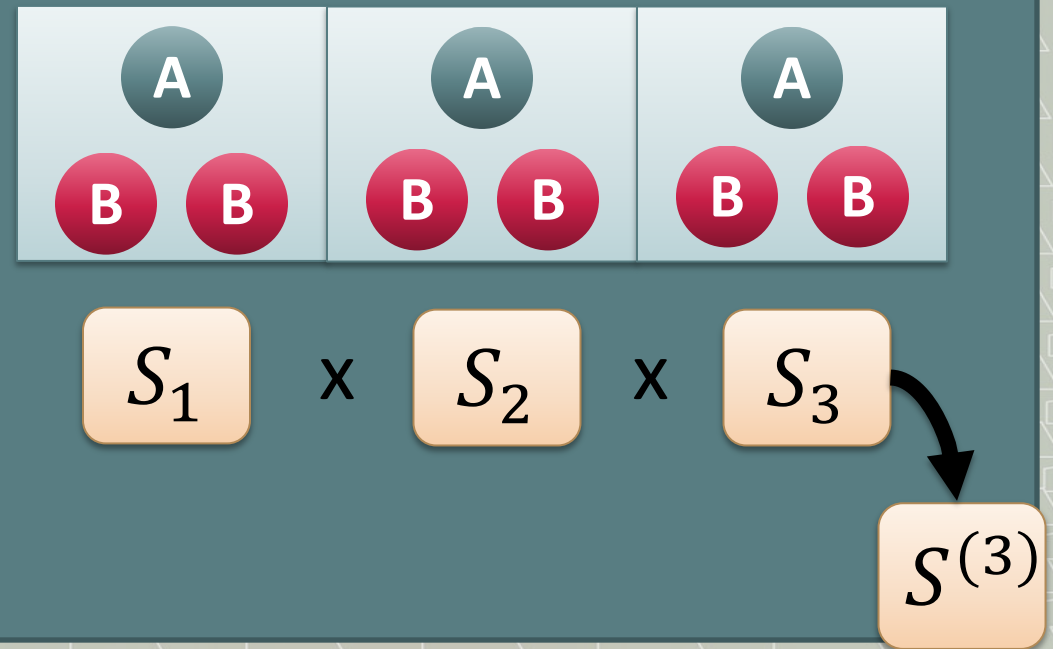
- Can make an **e-process**: multiply E-values for all data blocks

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

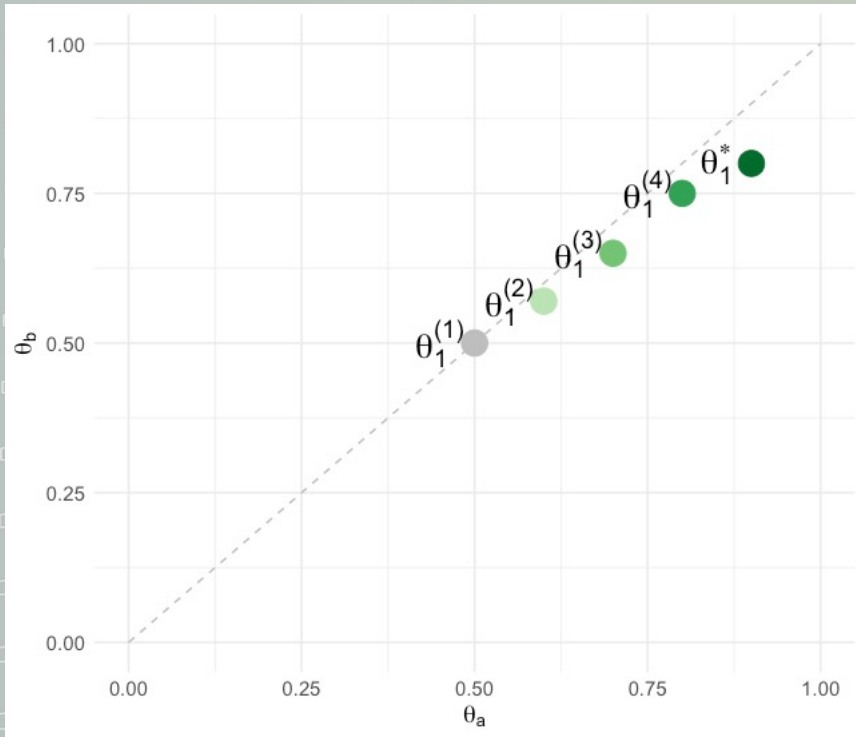
- For **arbitrary stopping rule** (E-value  $\geq 20$ , no money for further experiment, etc..):

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

Key: multiplying E-values yields another E-value

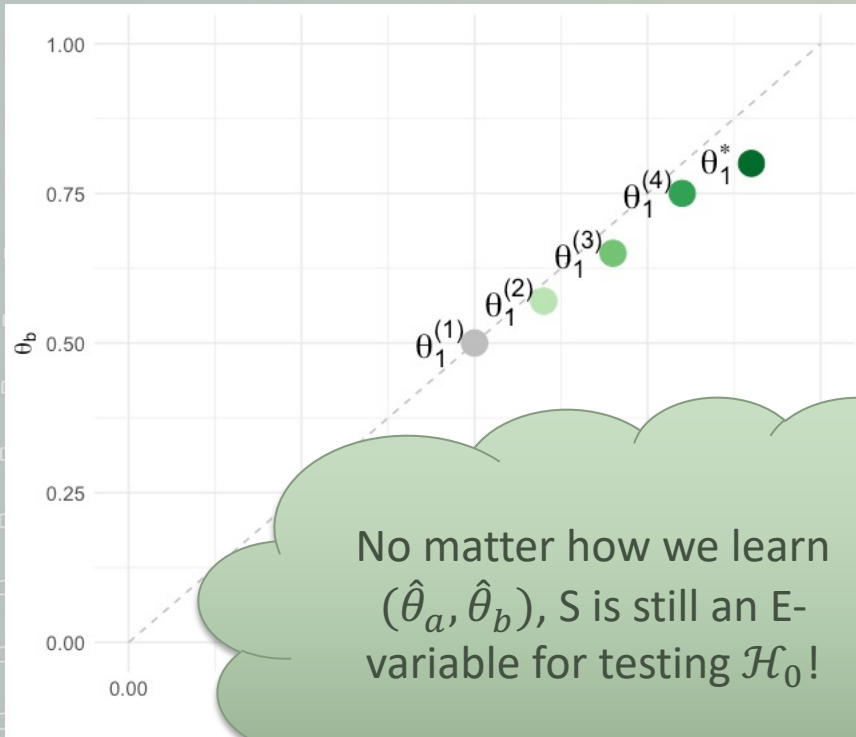


# Learn parameter for $\mathcal{H}_1$



- 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

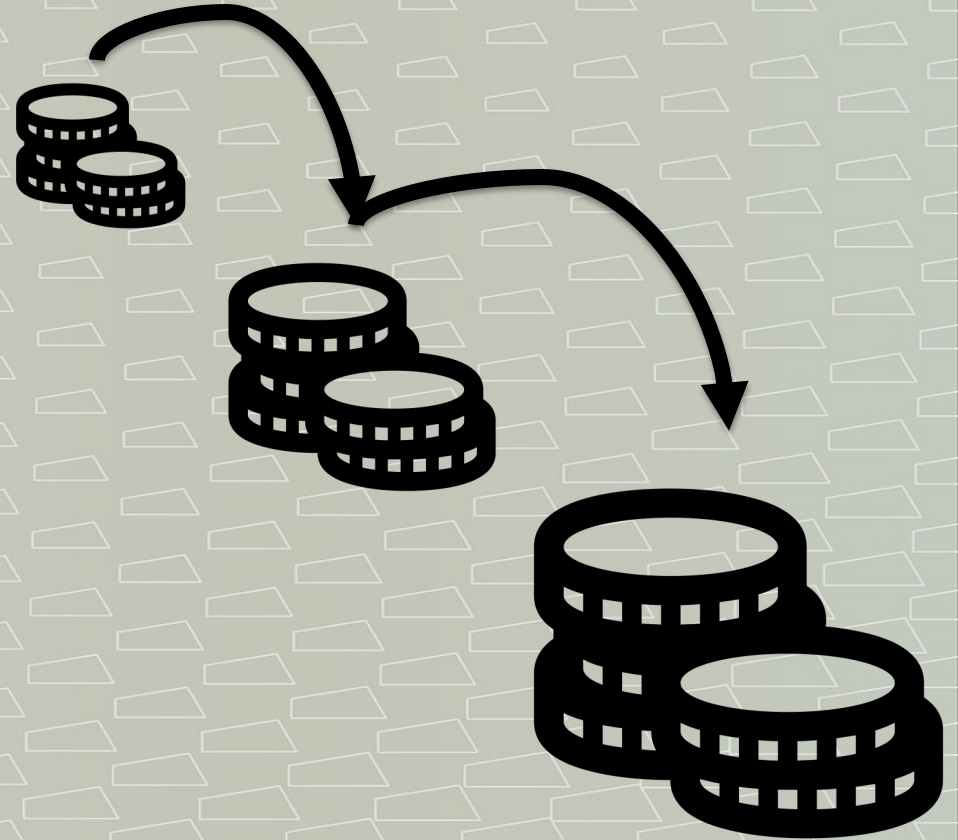
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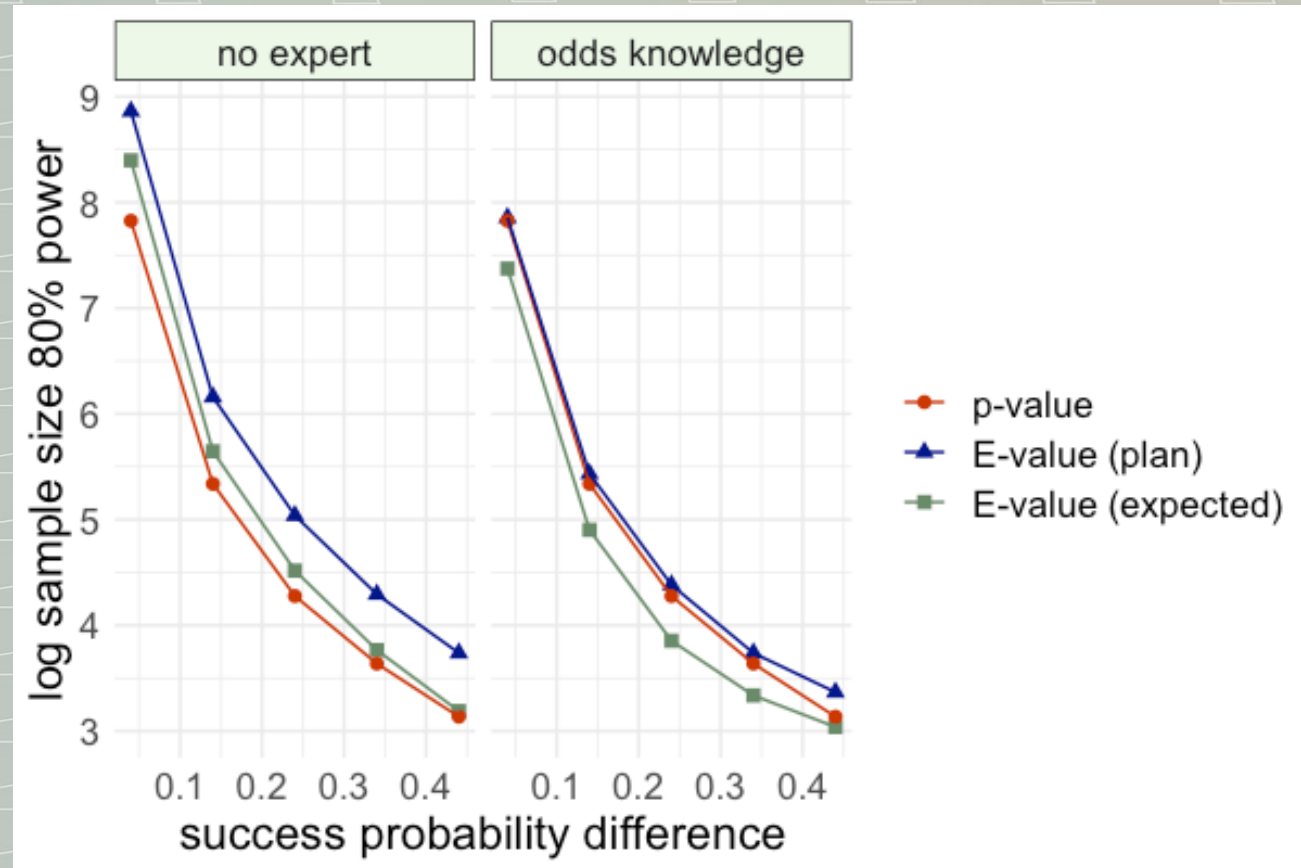
# Evidence against $\mathcal{H}_1$ and Type-II error

- **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

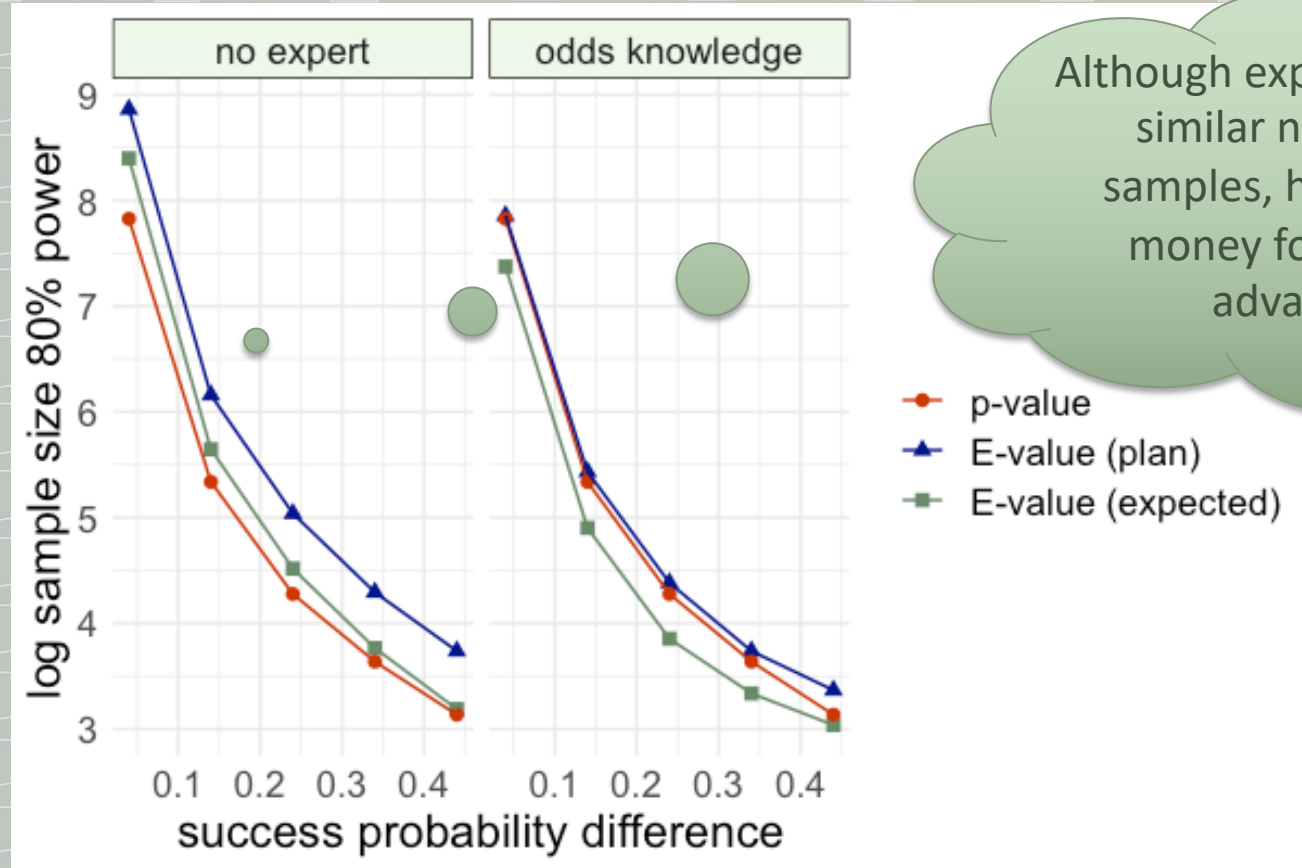




# 2x2 E-values vs classical counterpart



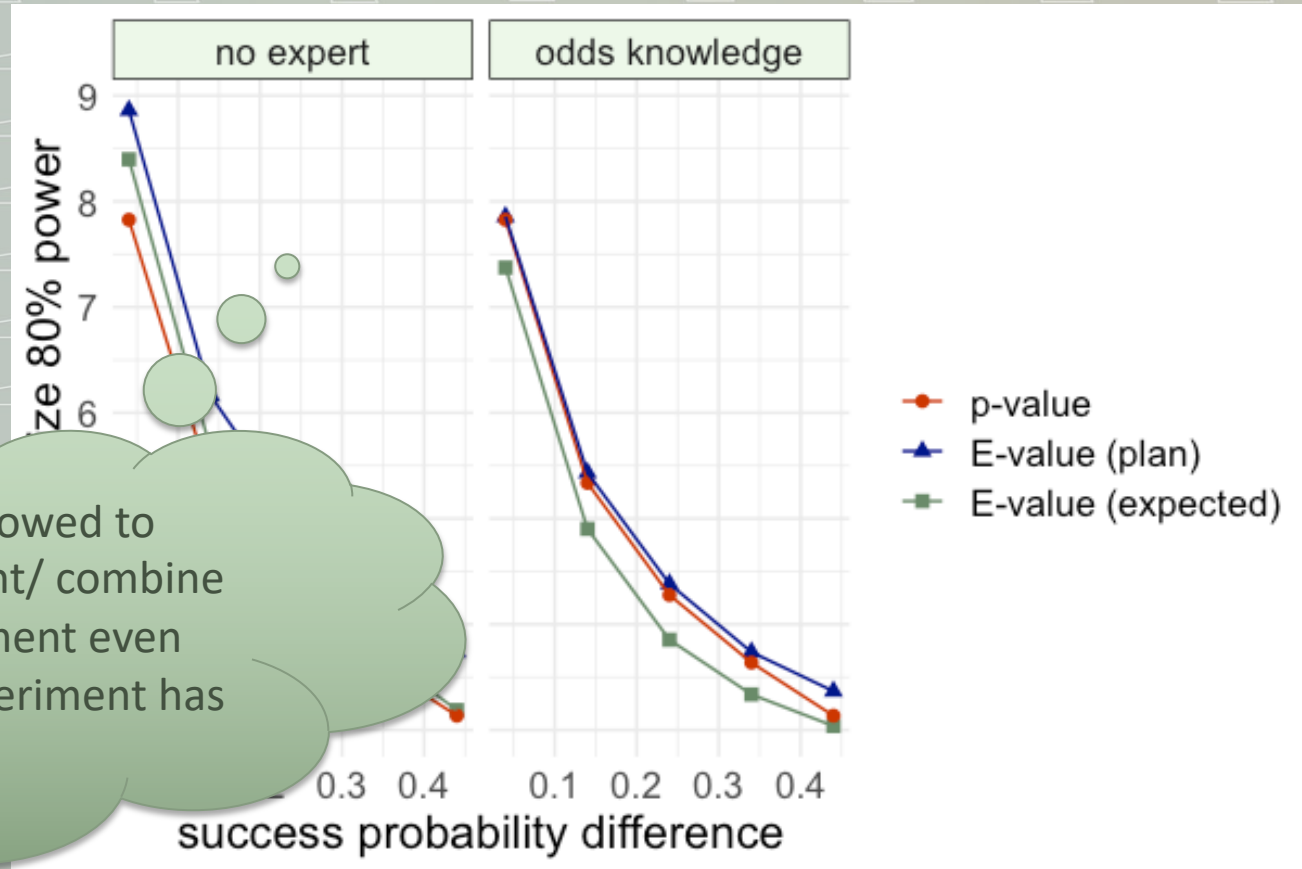
# 2x2 E-values vs classical counterpart



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

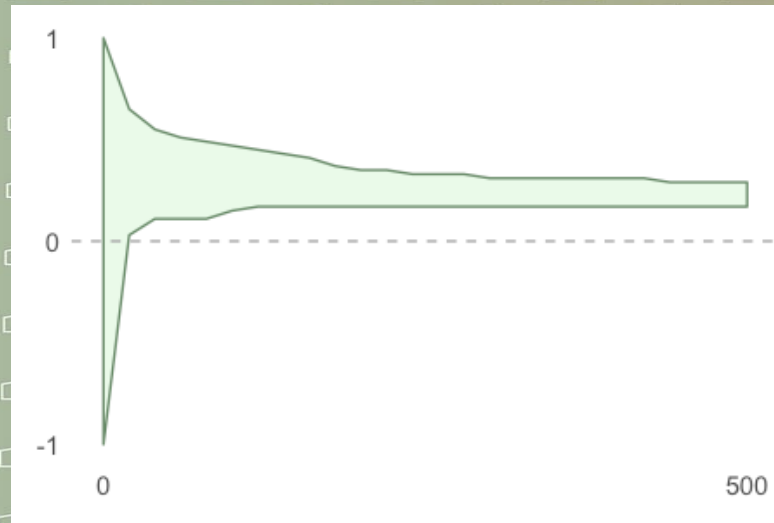
Figure adapted from Turner et al., 2021, figure 4

# 2x2 E-values vs classical counterpart



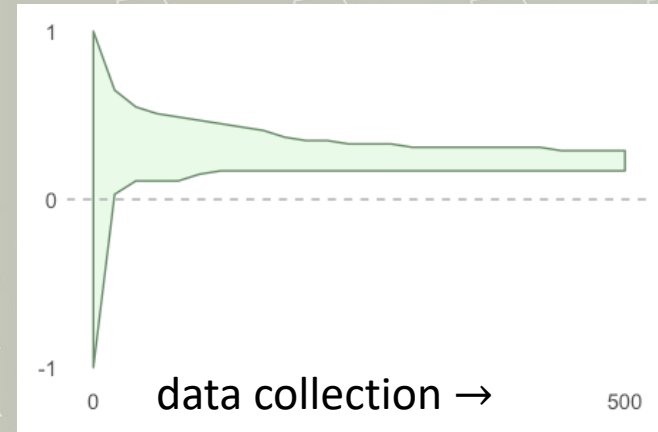
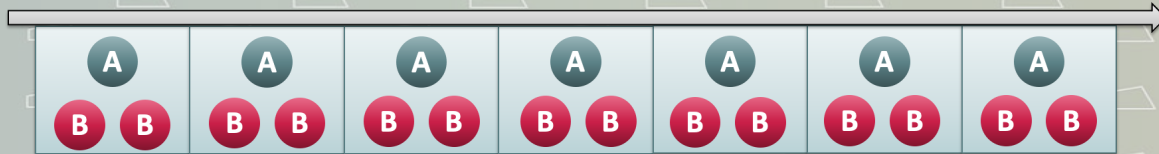
On plus side: allowed to continue experiment/ combine with new experiment even years after first experiment has ended!

# 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  $\alpha$  (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  $(1 - \alpha)$ .

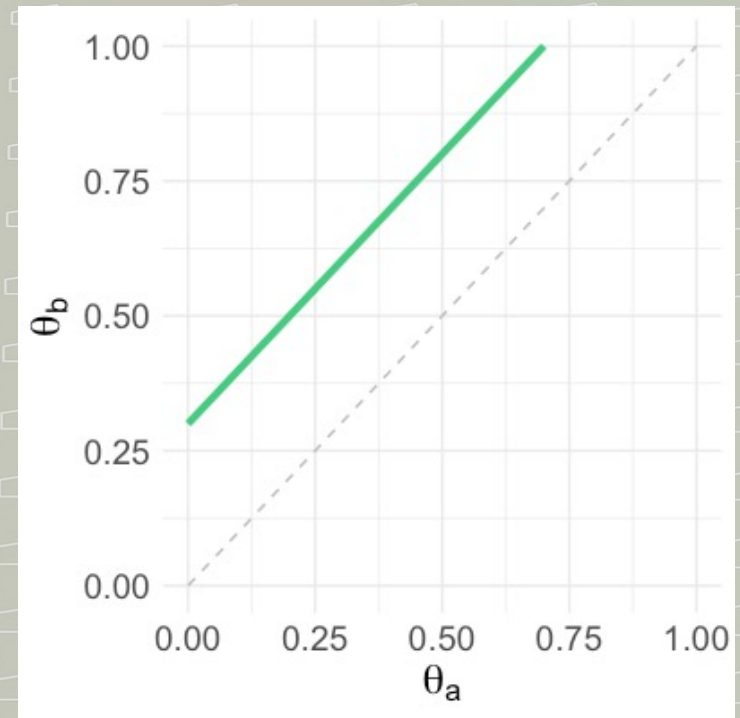
# Extension to $\mathcal{H}_0$ beyond $\theta_a = \theta_b$ : examples

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:  $\delta(\theta_a, \theta_b) = \frac{\theta_b}{1-\theta_b} \frac{1-\theta_a}{\theta_a}, \Gamma = \mathbb{R}^+$

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



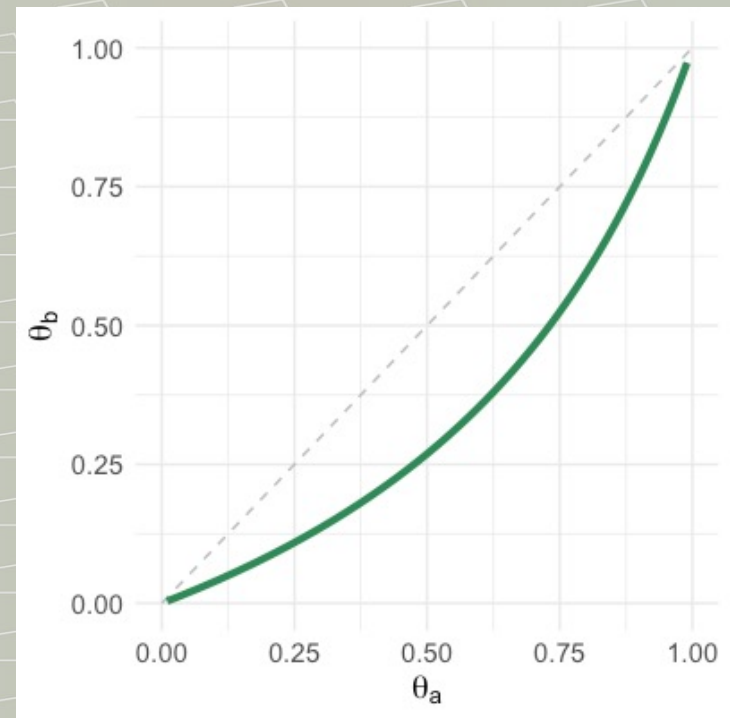
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– E.g. Odds Ratio:  $\delta(\theta_a, \theta_b) = \frac{\theta_b}{1-\theta_b} - \frac{1-\theta_a}{\theta_a}, \Gamma = \mathbb{R}^+$

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





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

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

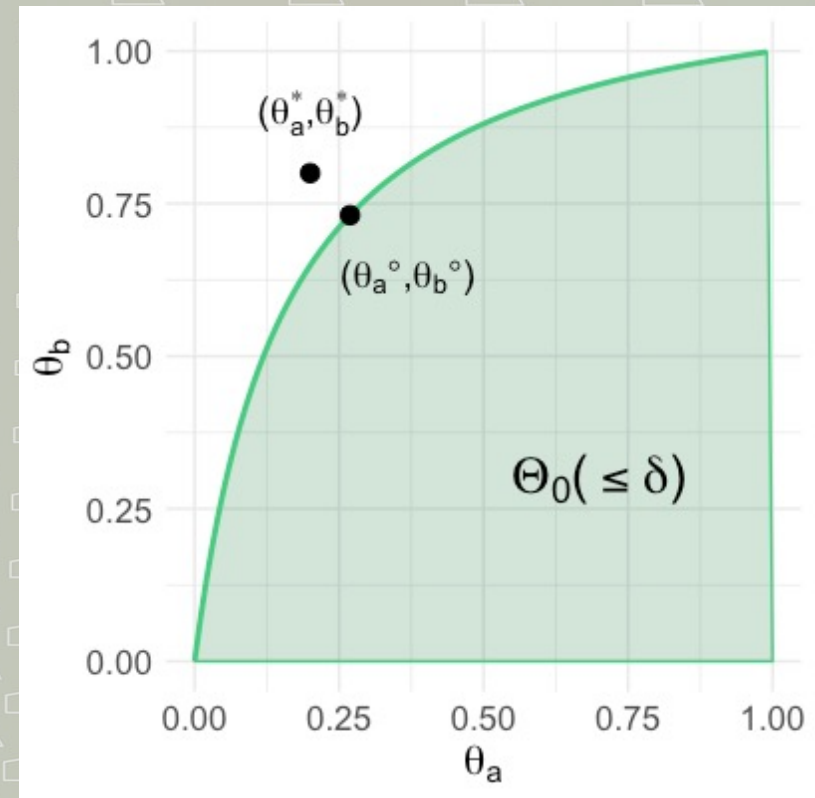
where  $(\theta_a^\circ, \theta_b^\circ)$  achieve

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

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

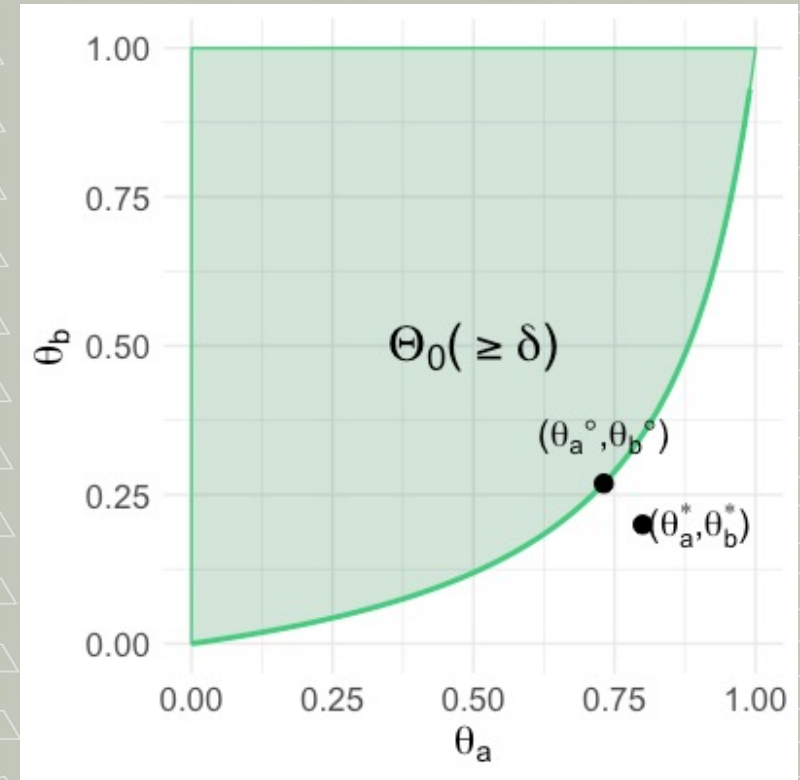
# Tricky case: odds ratio and convexity of $\mathcal{H}_0$

- 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

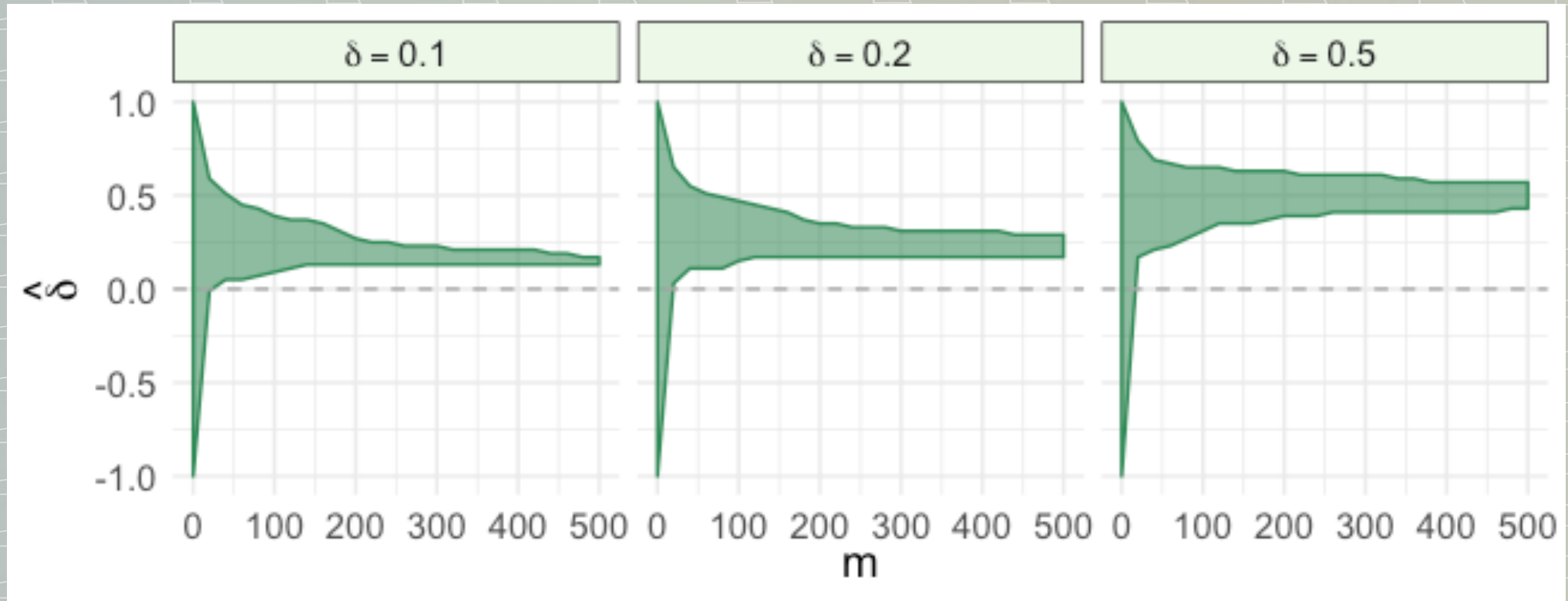


# Tricky case: odds ratio and convexity of $\mathcal{H}_0$

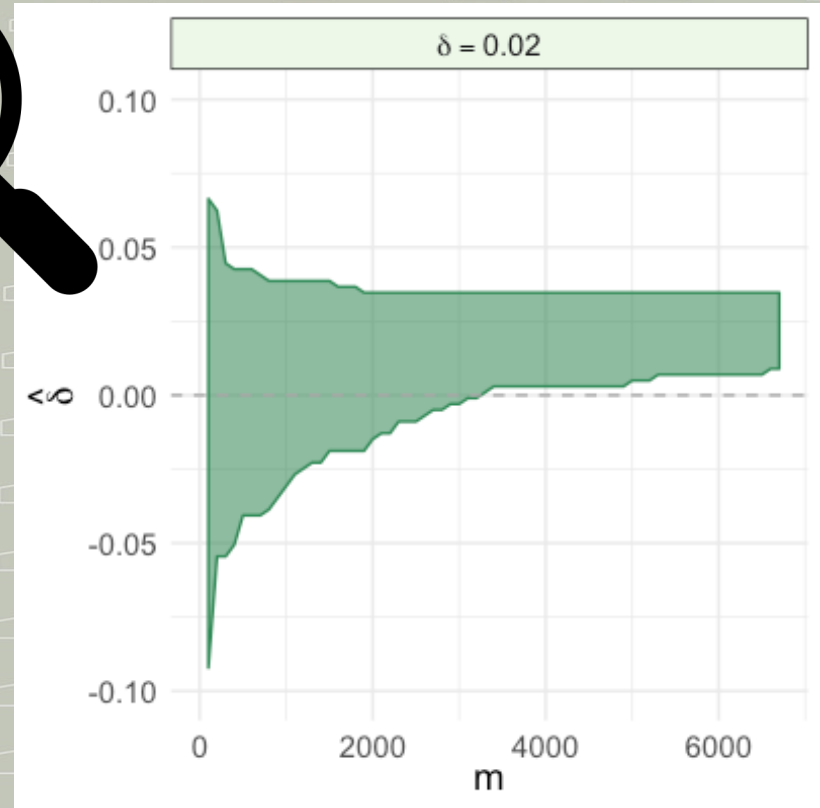
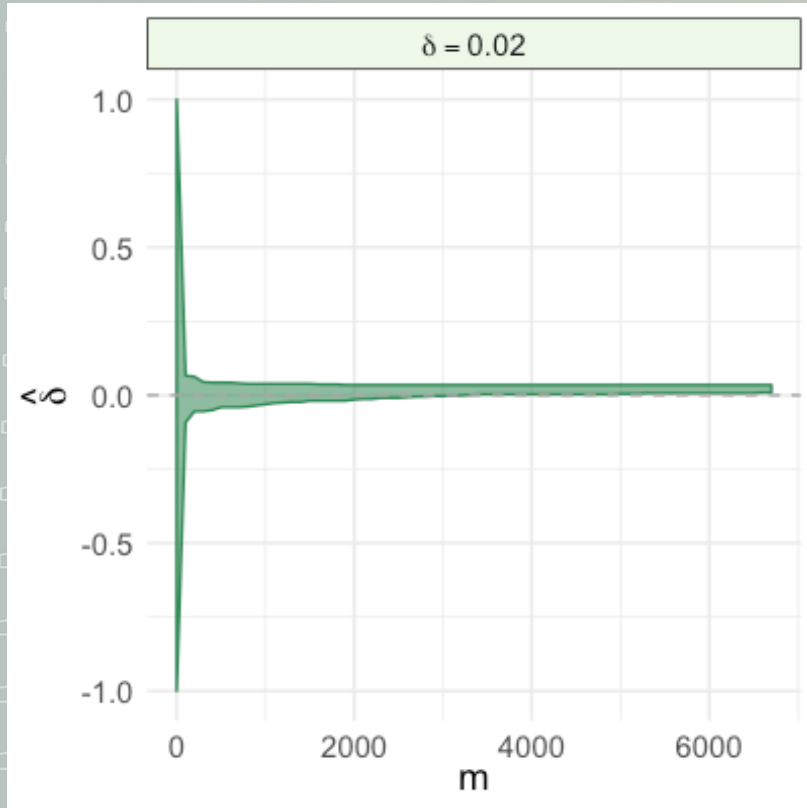
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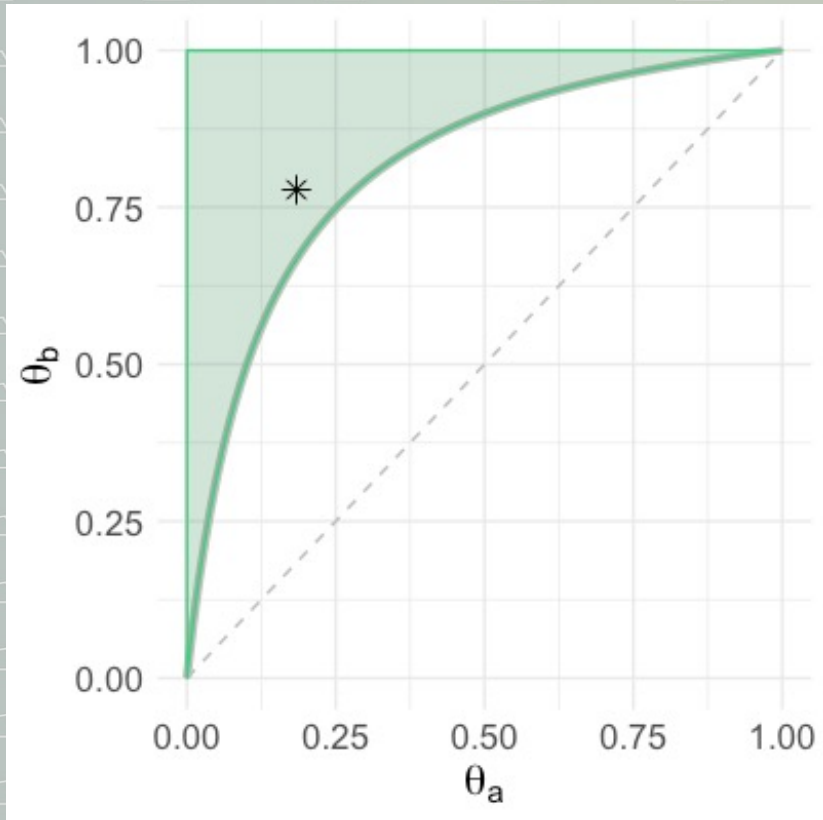
# Simulations: risk difference



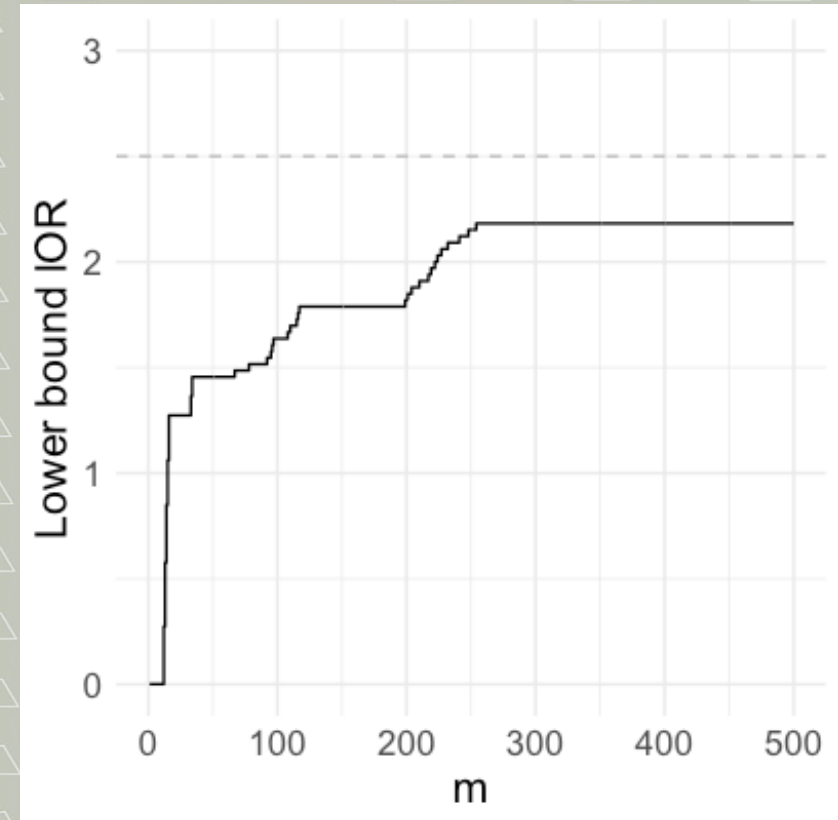
# Simulations: risk difference



# Simulation: log of the odds ratio

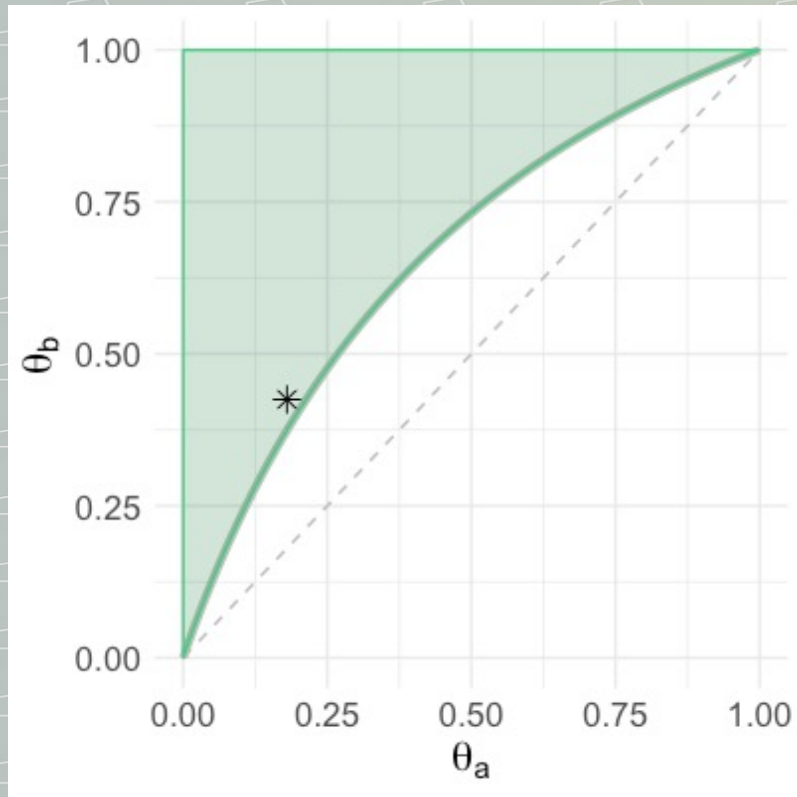


One-sided  $CS^+$  at data block  $m = 500$

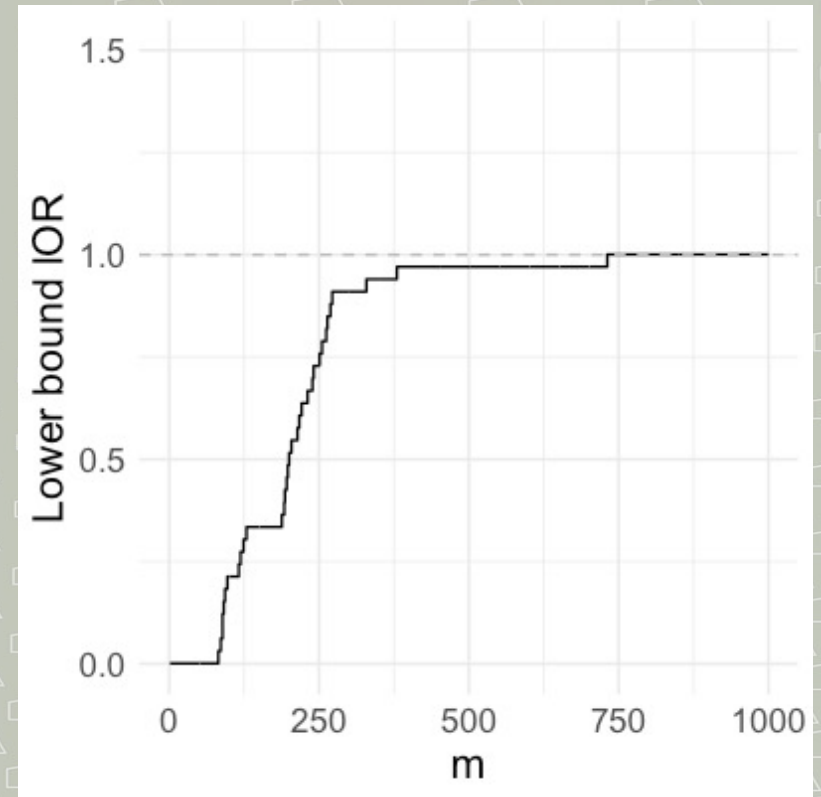


lower bound over time

# 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

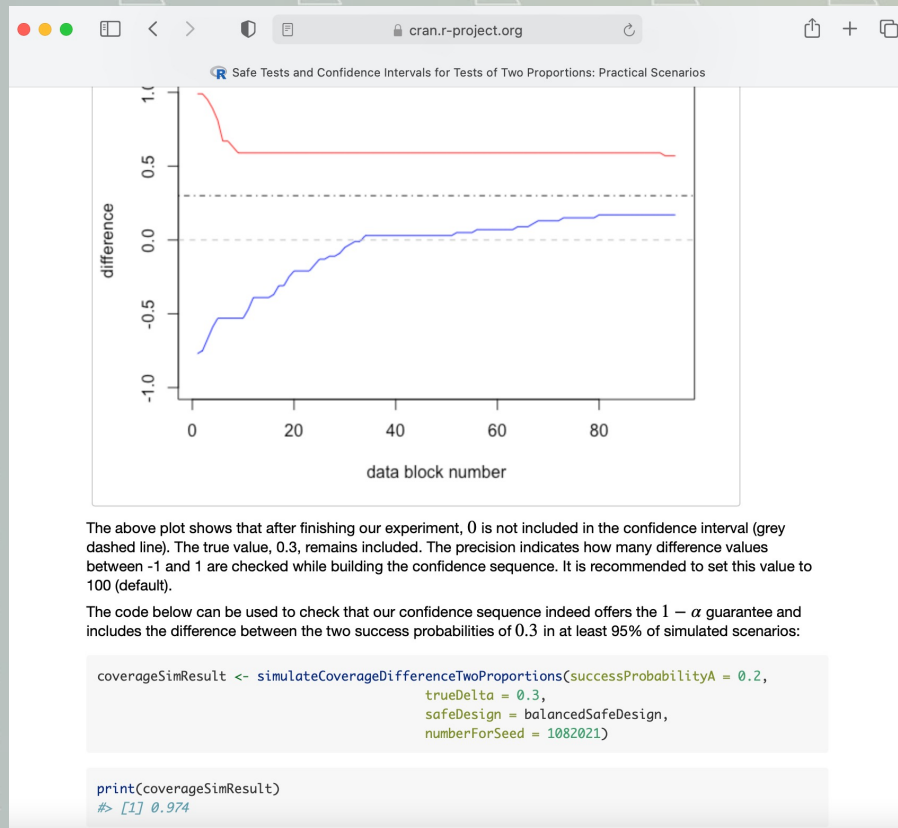


# Extensions

- 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>

# Extra slides

# Use case: Enabling Personalised Interventions project



Three major challenges limit optimal use of healthcare data<sup>1</sup>:

1. data is not accessible and remains in silos;
2. data is not analyzed correctly to yield proper clinical insights;
3. insights are not available to clinicians and patients to allow (self-)management of healthcare

# Implementation in psychiatry research/ recommender systems

“Given the underlying syndrome, age and gender of a patient, do we **estimate ECT treatment** to be more effective than pharmaceutical treatment?”

“Given age, gender, diagnosis and antidepressant treatment type of a patient, what will be the **effect of adding sleep medication** to treatment?”

