

Likelihood and its Discontents

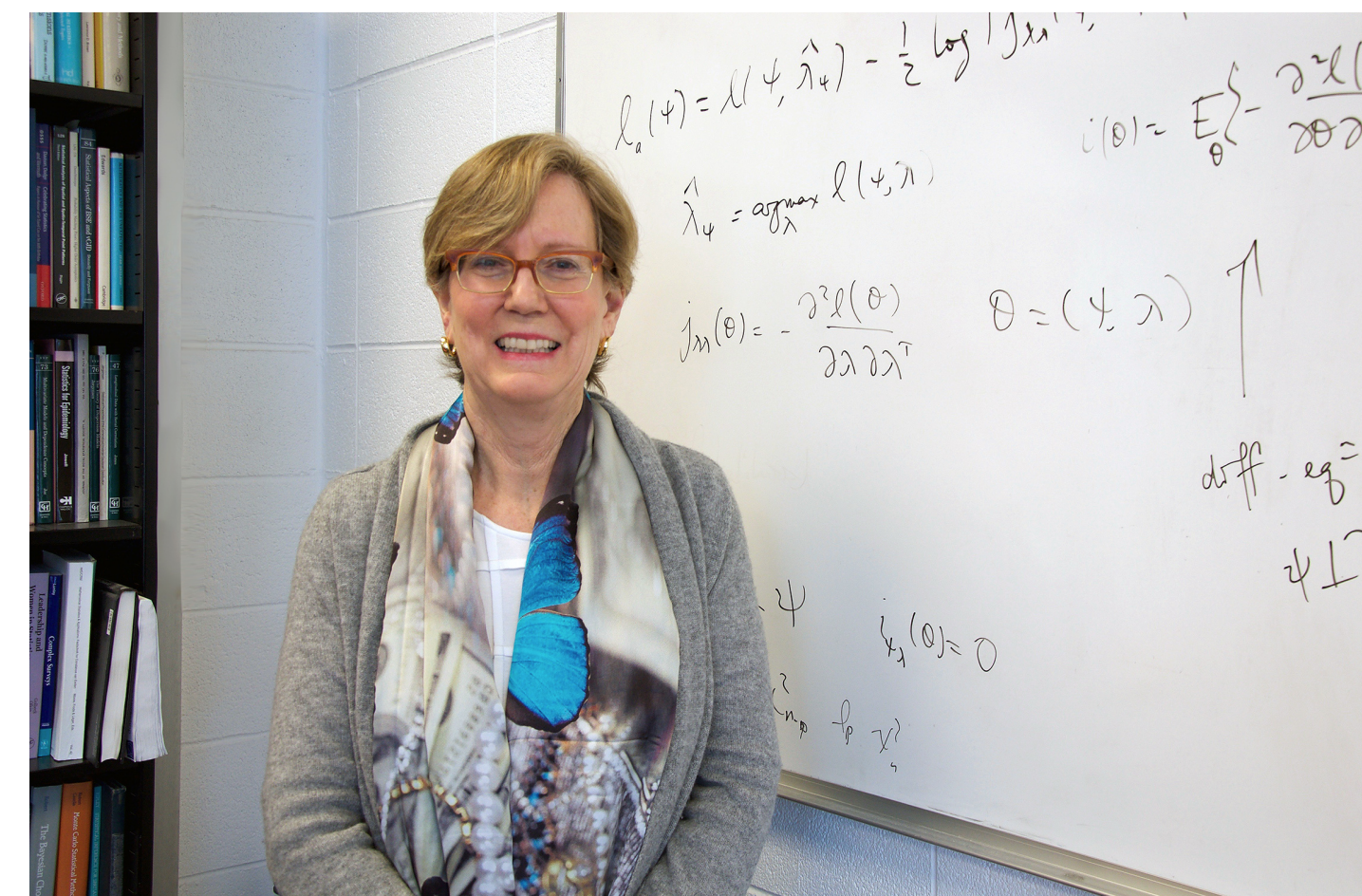
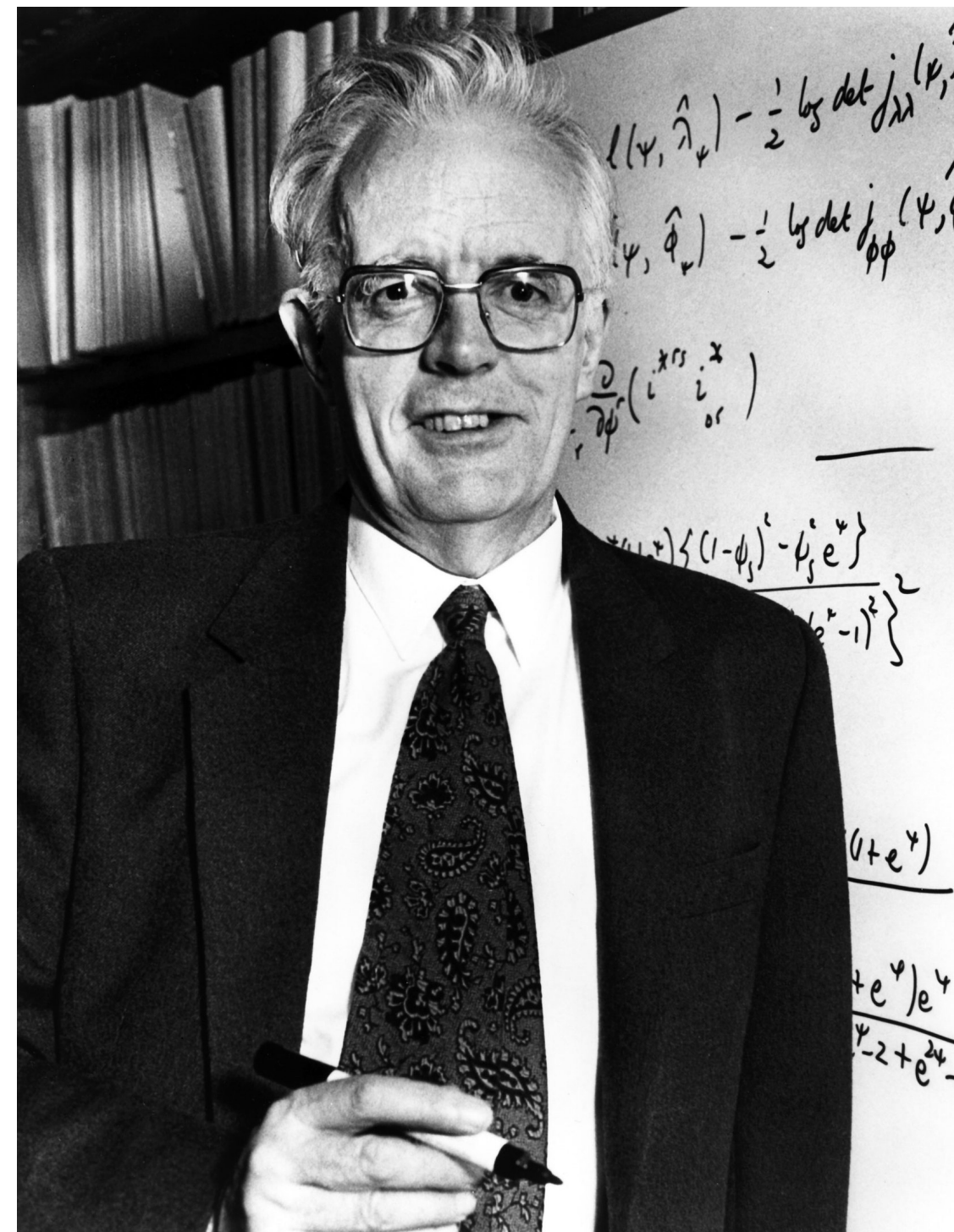
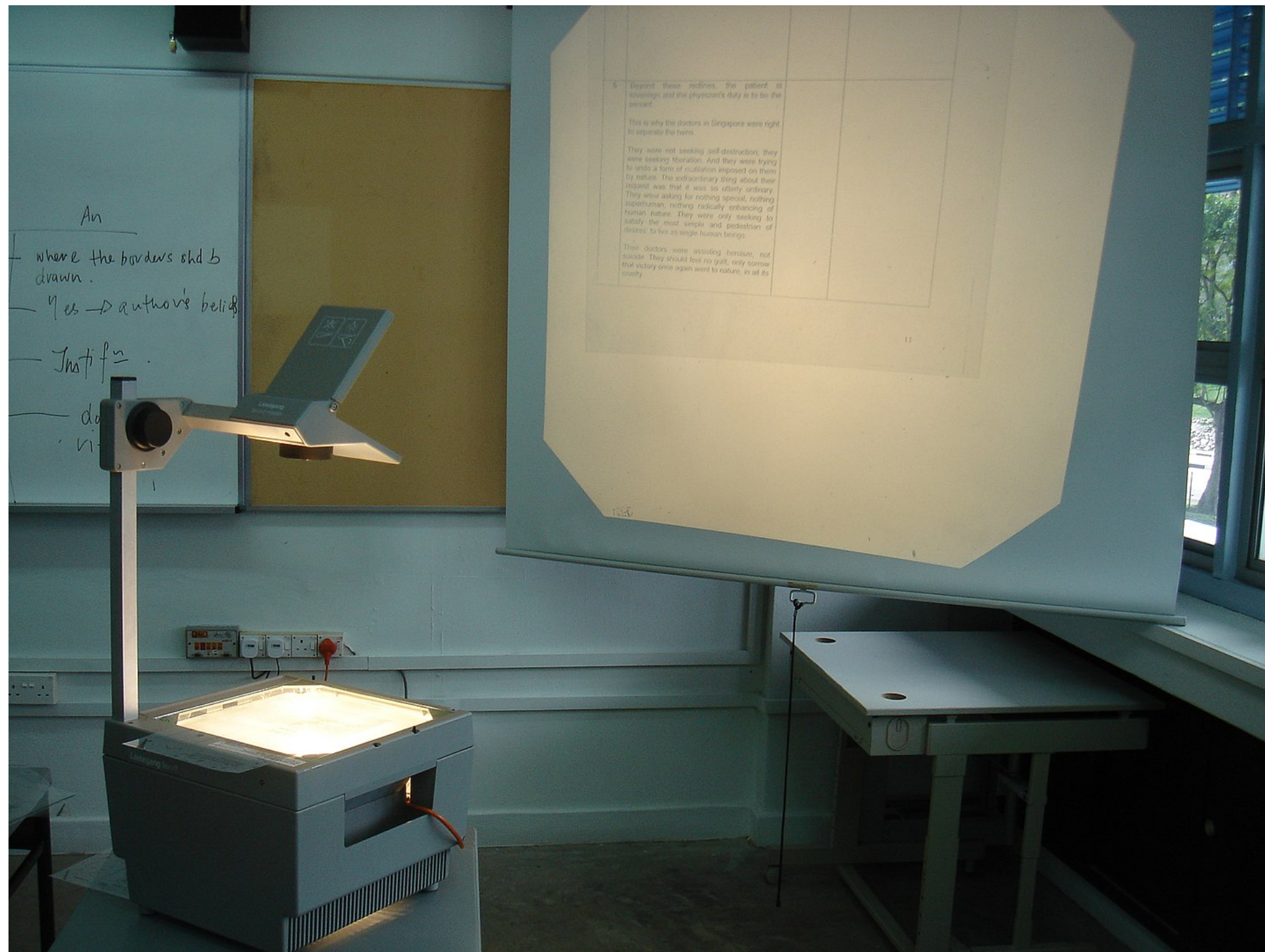
Nancy Reid
University of Toronto

August 10, 2022



JSM 1989

Probability models: their role in statistical analysis



JSM 1990

From likelihood to significance

How to go from $l(\theta)$ to $p(\theta)$

(ii) For general models

..... with θ as the given parameter

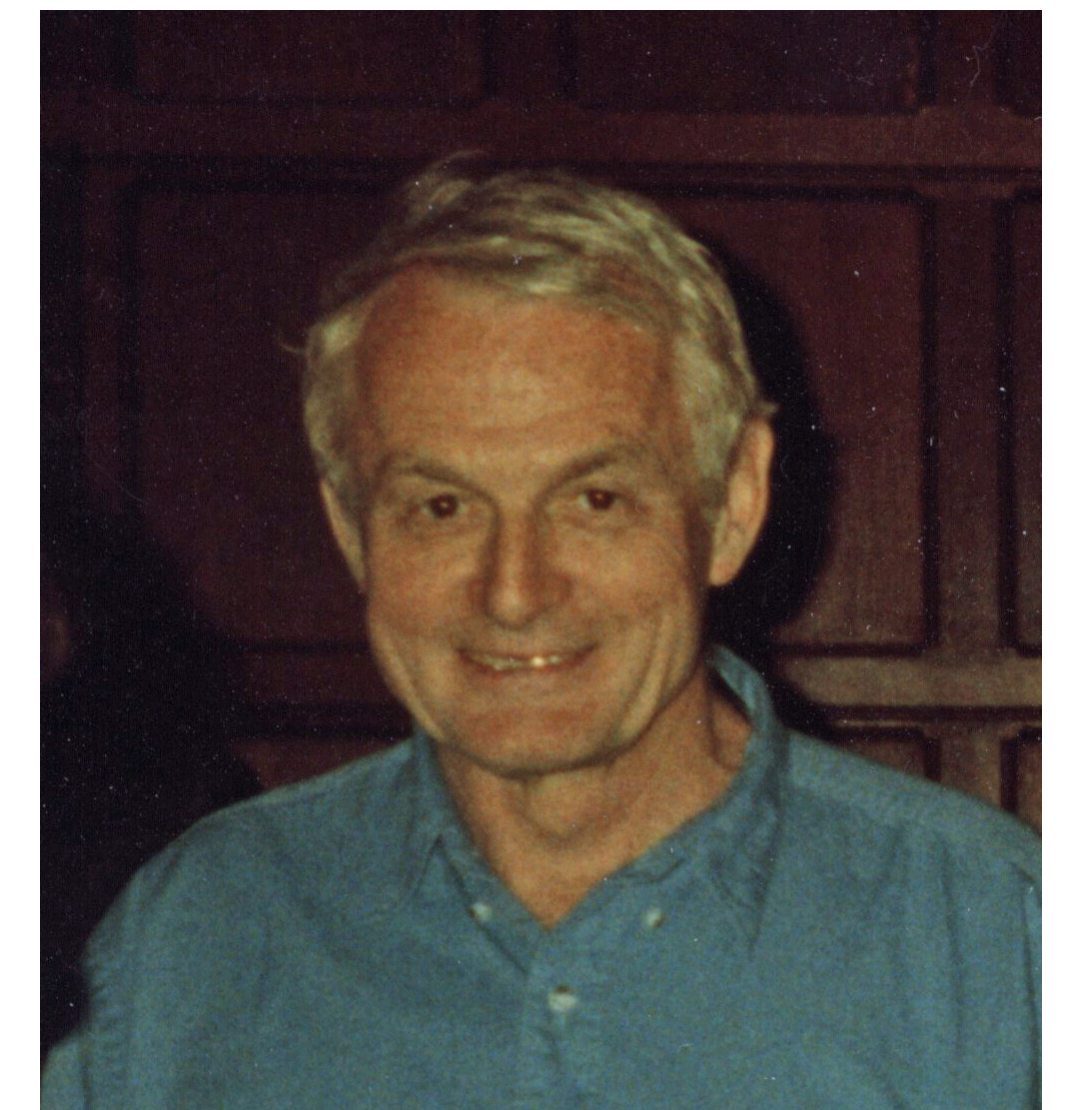
Make formula parameterization invariant F 1988

Construct a data-dependent parameter F & Reid 1990

The 'new' parameter is

$$\phi = \dot{l}(\theta; y)|_{y=y^*} = \frac{d}{dy} l(\theta; y)|_{y=y^*}$$

SP 0:34:07



JSM 1990

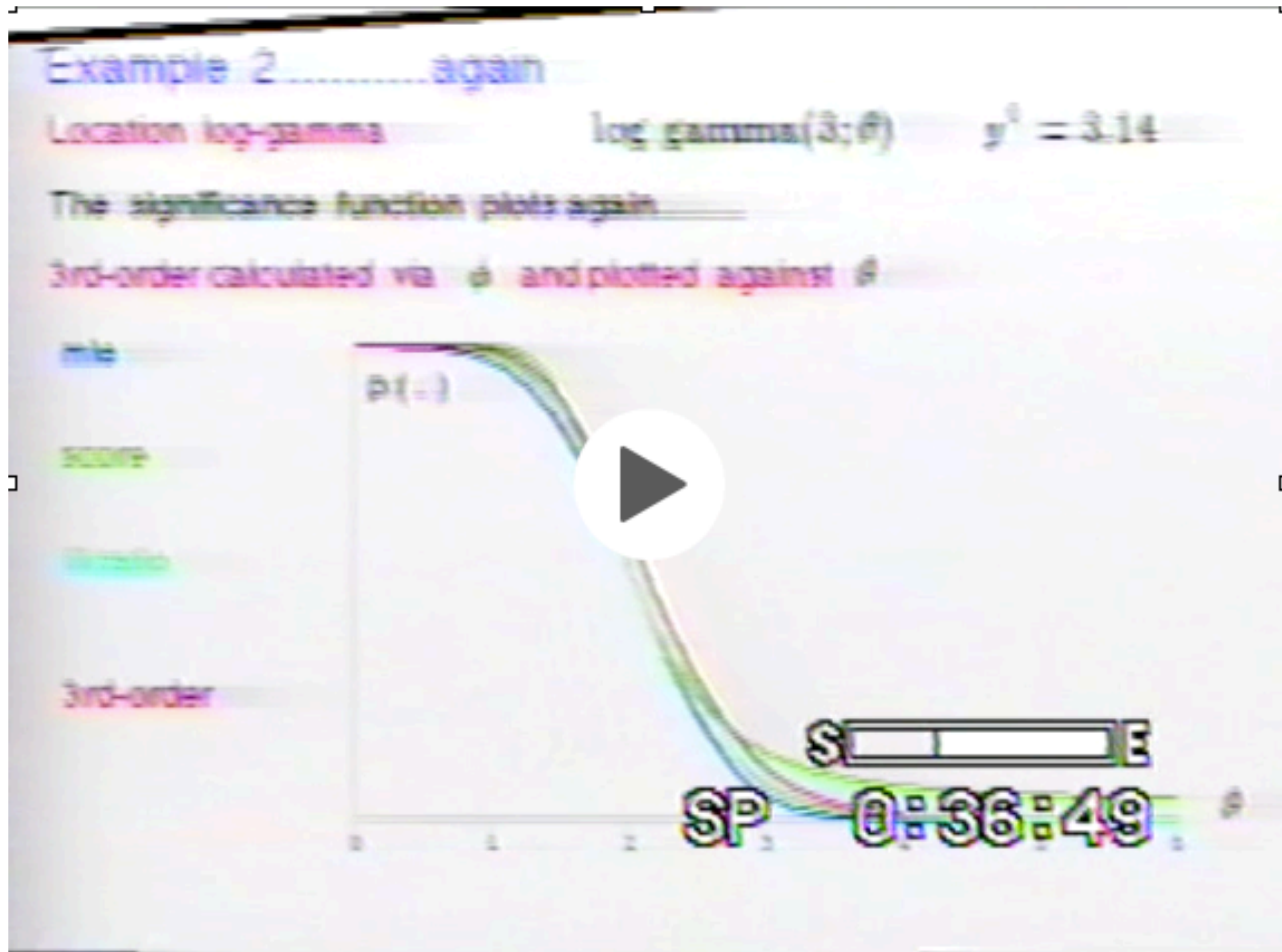
Example 2.....again

Location log-gamma $\log \text{gamma}(3; \theta) \quad y^0 = 3.14$

SE
SP 0:36:24



JSM 1990



Outline

1. Likelihood inference
2. The discontents
3. Theory and applications

1. Likelihood inference

Some notation

Model

$$y \sim f(\cdot; \theta), \quad \theta \in \Theta$$

Data

$$y_1, \dots, y_n \quad \text{independent}$$

Likelihood function

$$L(\theta; \underline{y}) \propto f(\underline{y}; \theta) = \prod_{i=1}^n f(y_i; \theta)$$

Log-likelihood function

$$\ell(\theta; y) = \log L(\theta; y) = \sum_{i=1}^n \log f(y_i; \theta)$$

Maximum Likelihood Estimator

$$\hat{\theta} = \arg \sup \ell(\theta; y)$$

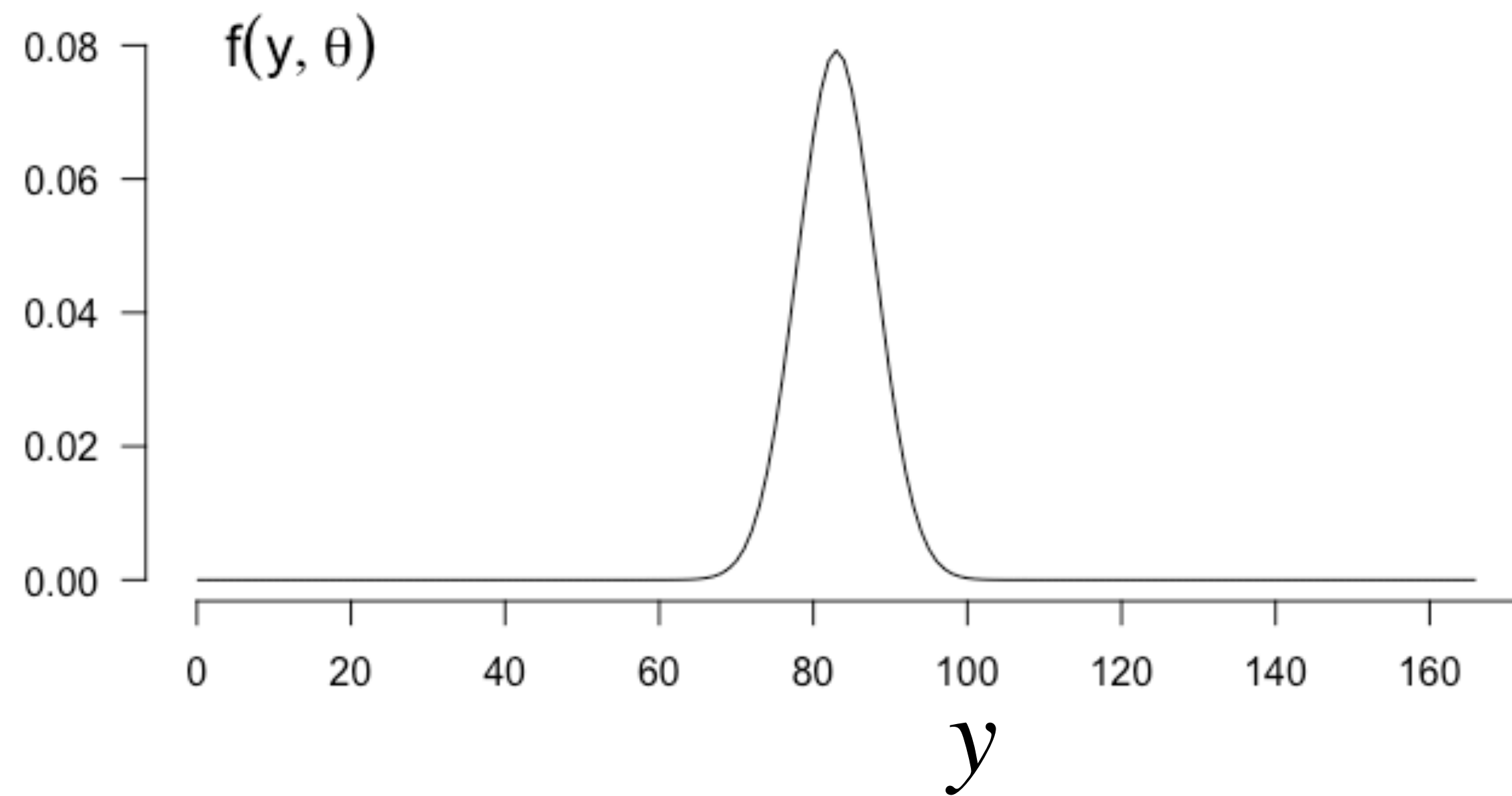
Profile likelihood function

$$L_{prof}(\psi) = L(\psi, \hat{\lambda}_{\psi}) \quad \theta = (\psi, \lambda) \quad \text{Constrained max. lik. est.}$$

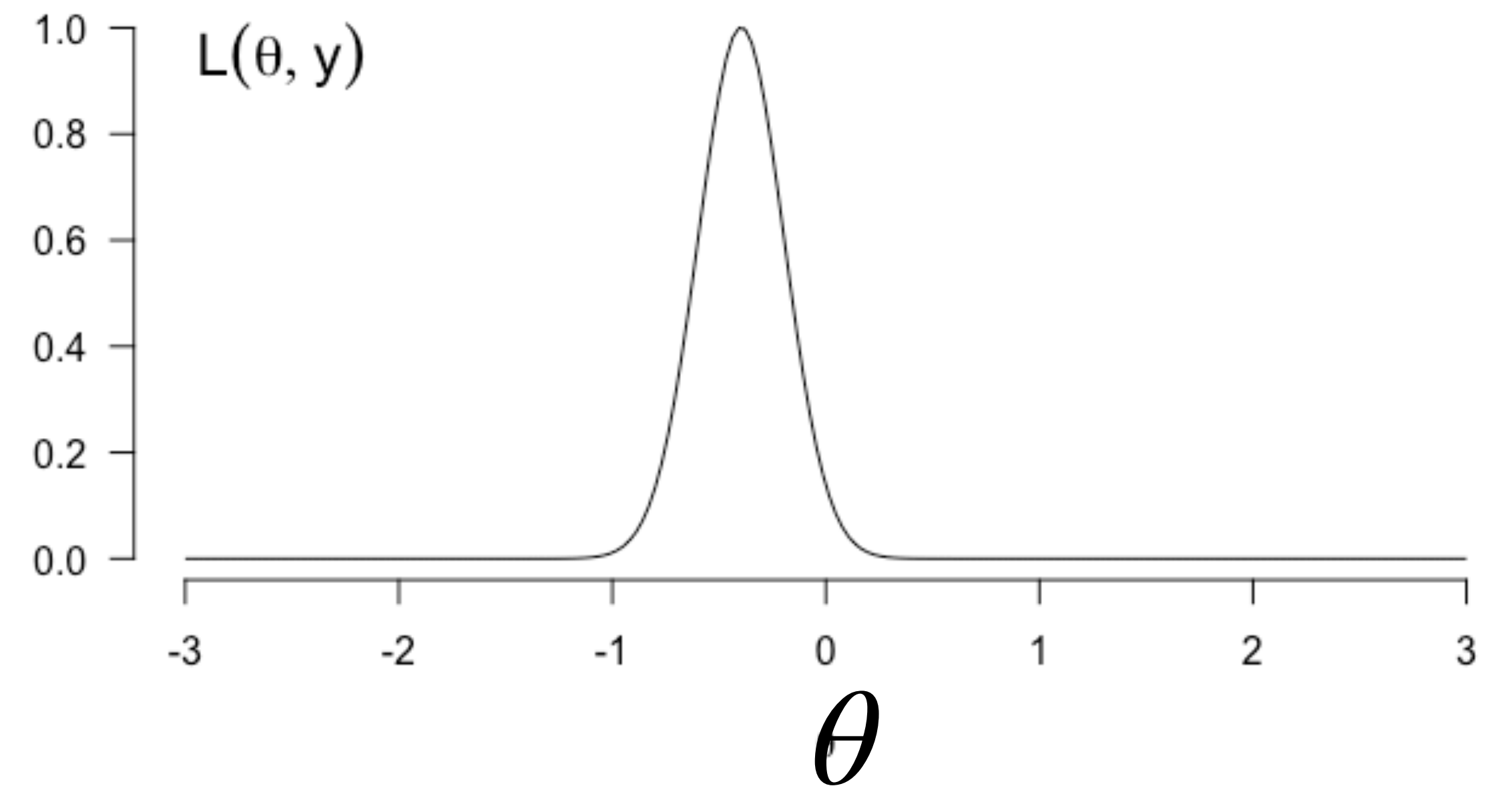
The likelihood function

Fisher 1922

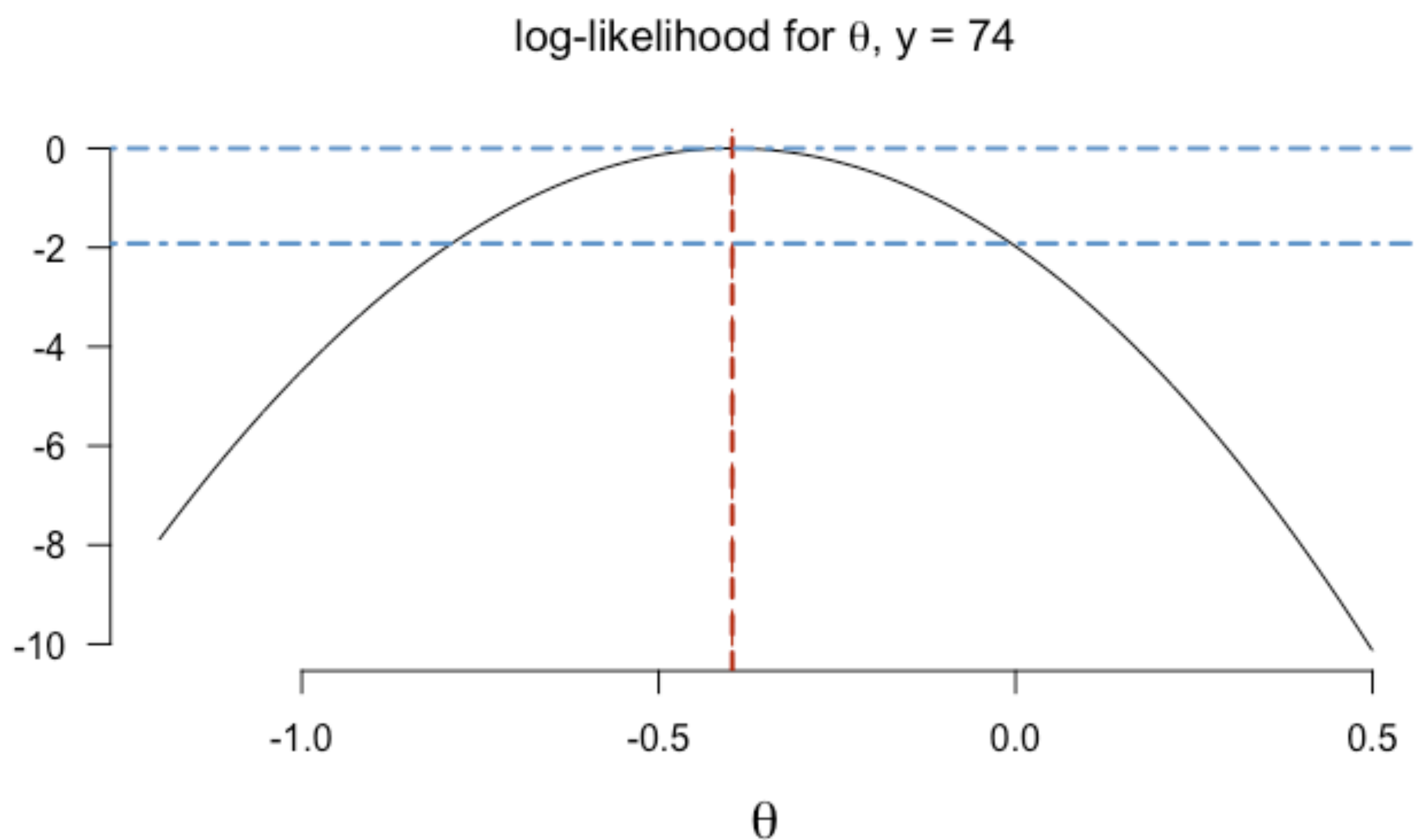
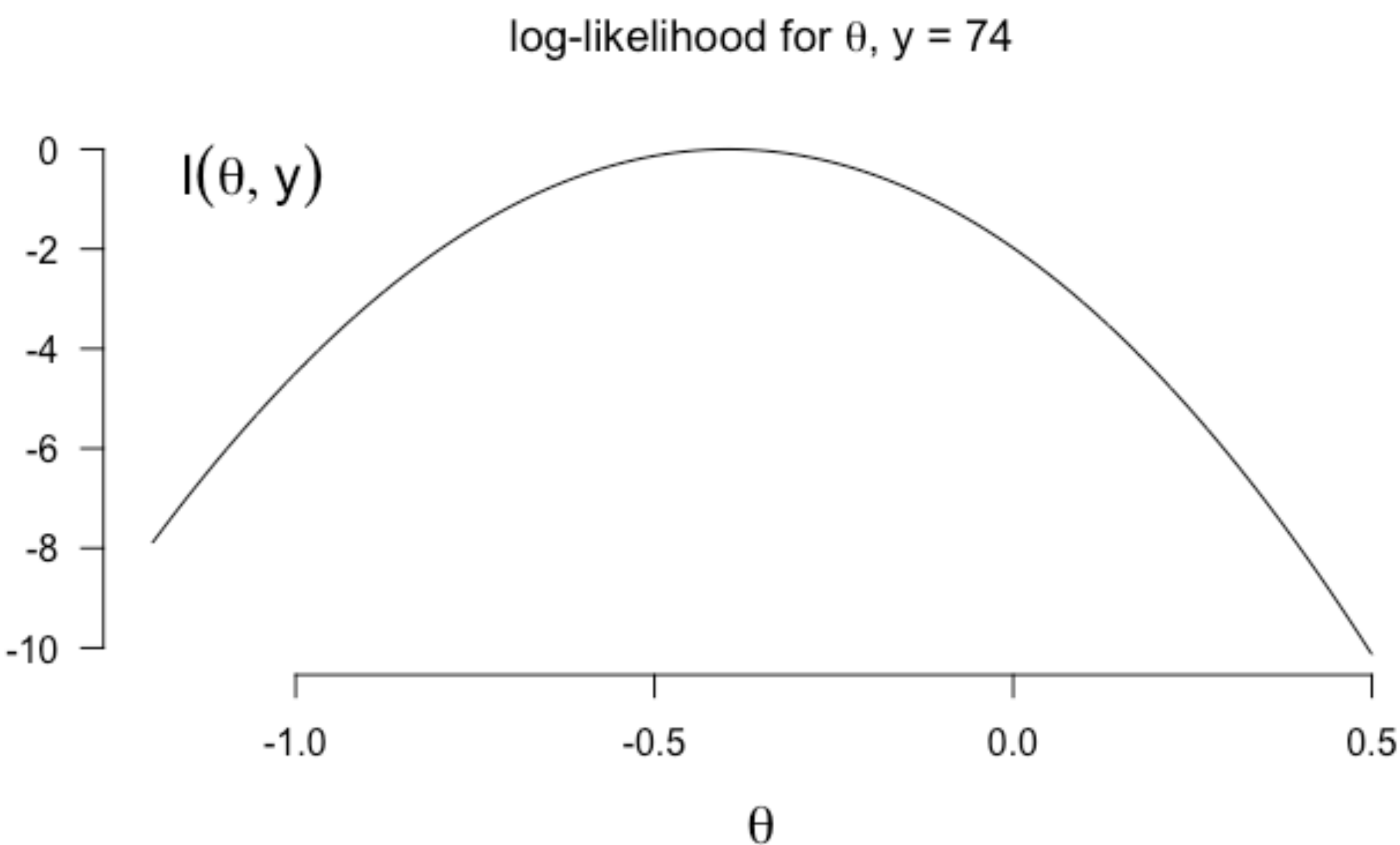
density of y , $\theta = 0$



likelihood of θ , $y = 74$



Likelihood inference



	Died	Lived	
New	74	138	212
Old	92	120	212
Total	166	258	424

2-sided p -value = 0.07

likelihood ratio test
no adjustment for covariates

$$\hat{\theta} \pm 1.96 \hat{\sigma}_{\theta}$$

$$(-0.75, +0.03)$$

Profile log-likelihood:

$$2\{\ell(\hat{\theta}) - \ell(\theta)\} = 3.84$$

$$(-0.72, +0.03)$$

$$2\{\ell_{prof}(\hat{\psi}) - \ell_{prof}(\psi)\} = 3.84$$

Haphazard selection

Recent literature

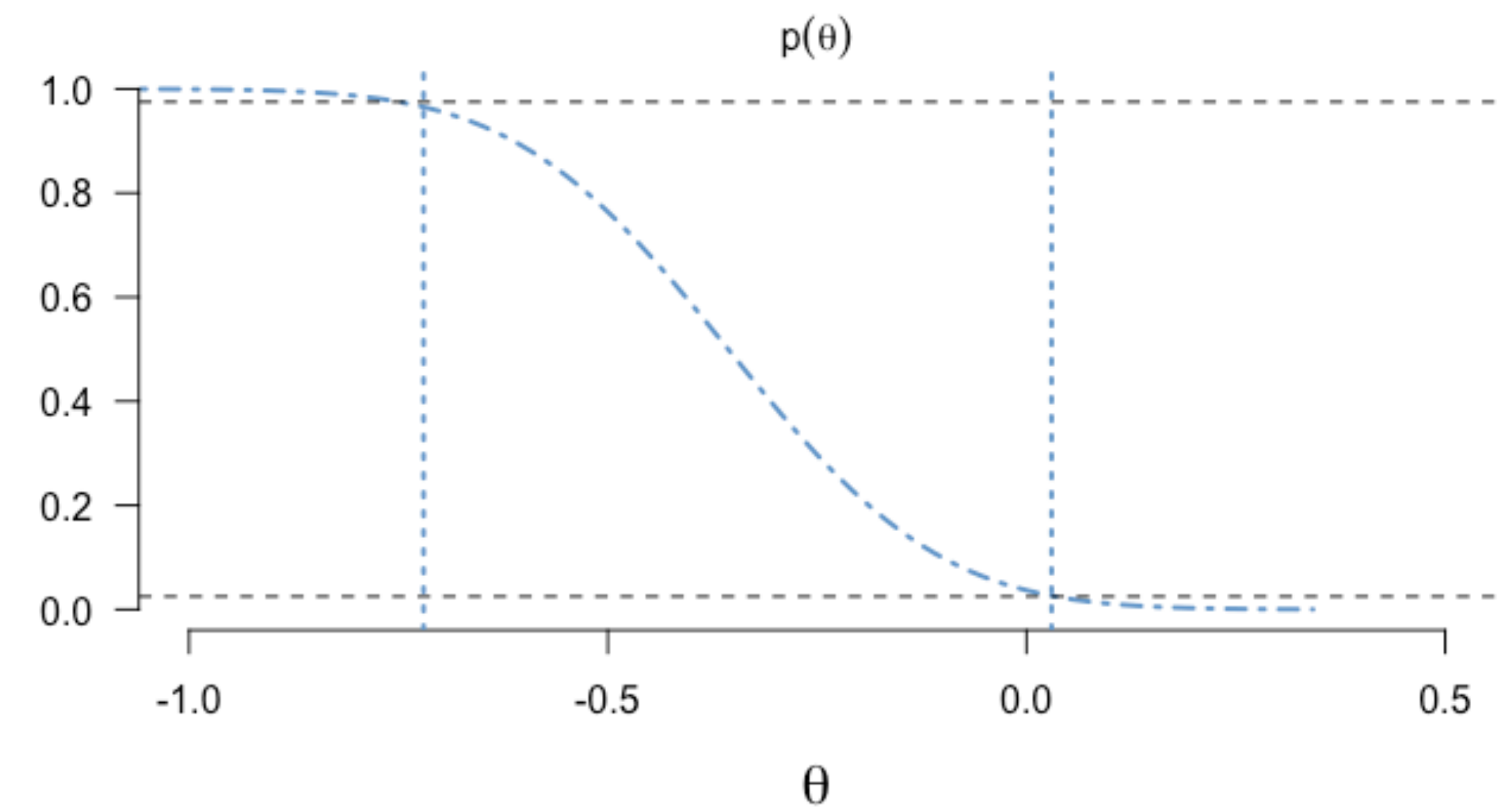
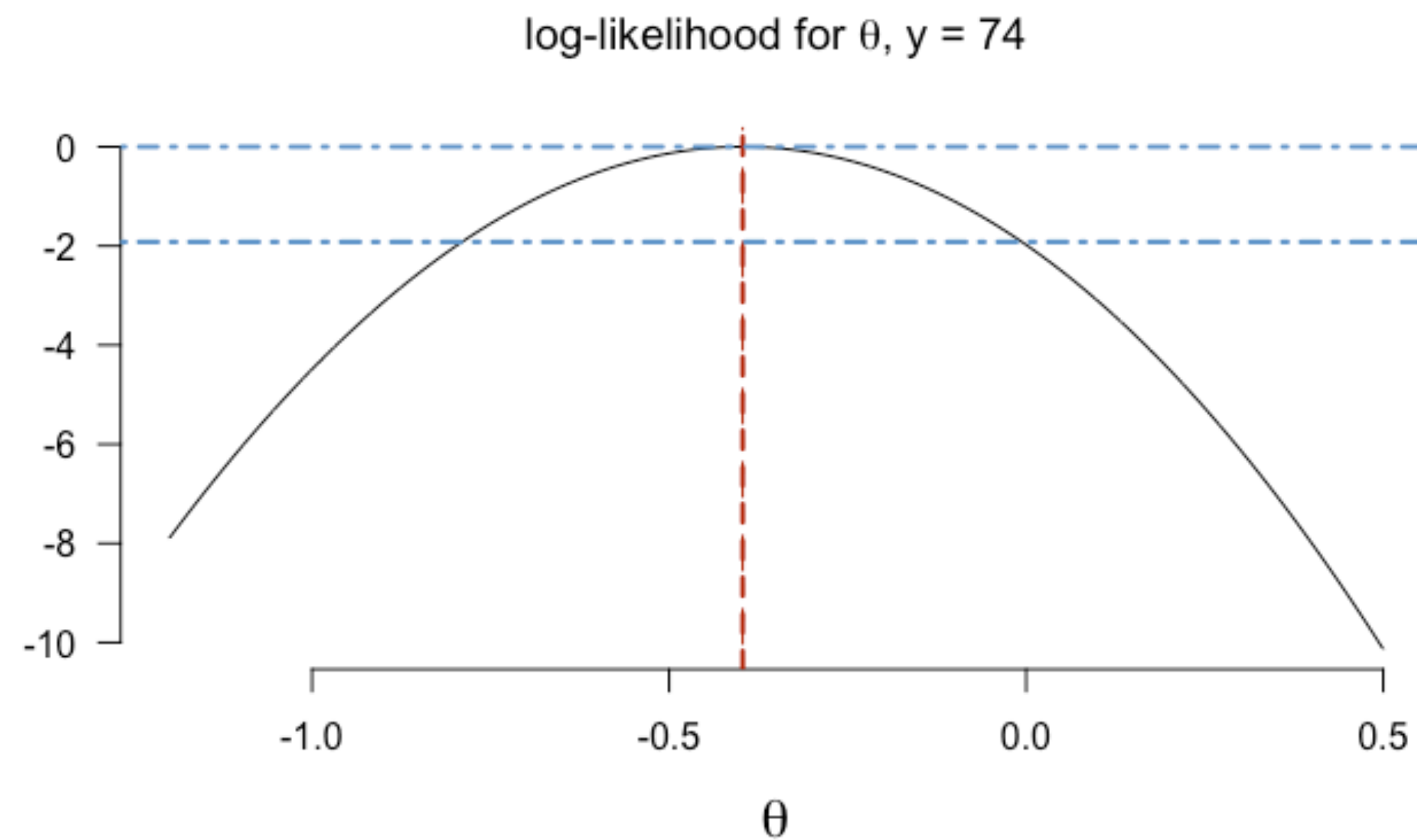
- “Likelihood-based inference for partially observed epidemics ...” Bu et al *JASA* 2022
- “Likelihood-based bacterial identification approach ...” Ryu *AoAS* 2022
- “Likelihood-based model selection for stochastic block models” Wang & Bickel *AoS* 2022
- “Graphical models for extremes” Engelke & Hitz *JRSS B* 2022
- “General maximum likelihood empirical Bayes ...” Jiang & Zhang *AoS* 2010

Why so useful?

- **Puts modelling first** $L(\theta; y) \propto f(y; \theta), \quad \theta \in \Theta$
- Provides **reliable** summary measures
 - maximum likelihood estimate, likelihood ratio test
- Can be converted to a probability, using Bayesian arguments
- Can be penalized to encourage variable selection or avoid over-fitting With a prior
- Can be converted to a significance function, using asymptotic theory Lasso +

Converting likelihood to significance

- Limit theory $q(\theta) = (\hat{\theta} - \theta)j^{1/2}(\hat{\theta}) \rightarrow N(0,1)$ $r(\theta) = \pm [2\{\ell(\hat{\theta}) - \ell(\theta)\}]^{1/2} \rightarrow N(0,1)$
- Significance function $p(\theta) \approx \Phi\{q(\theta)\}$ $p(\theta) \approx \Phi\{r(\theta)\}$ normal cdf

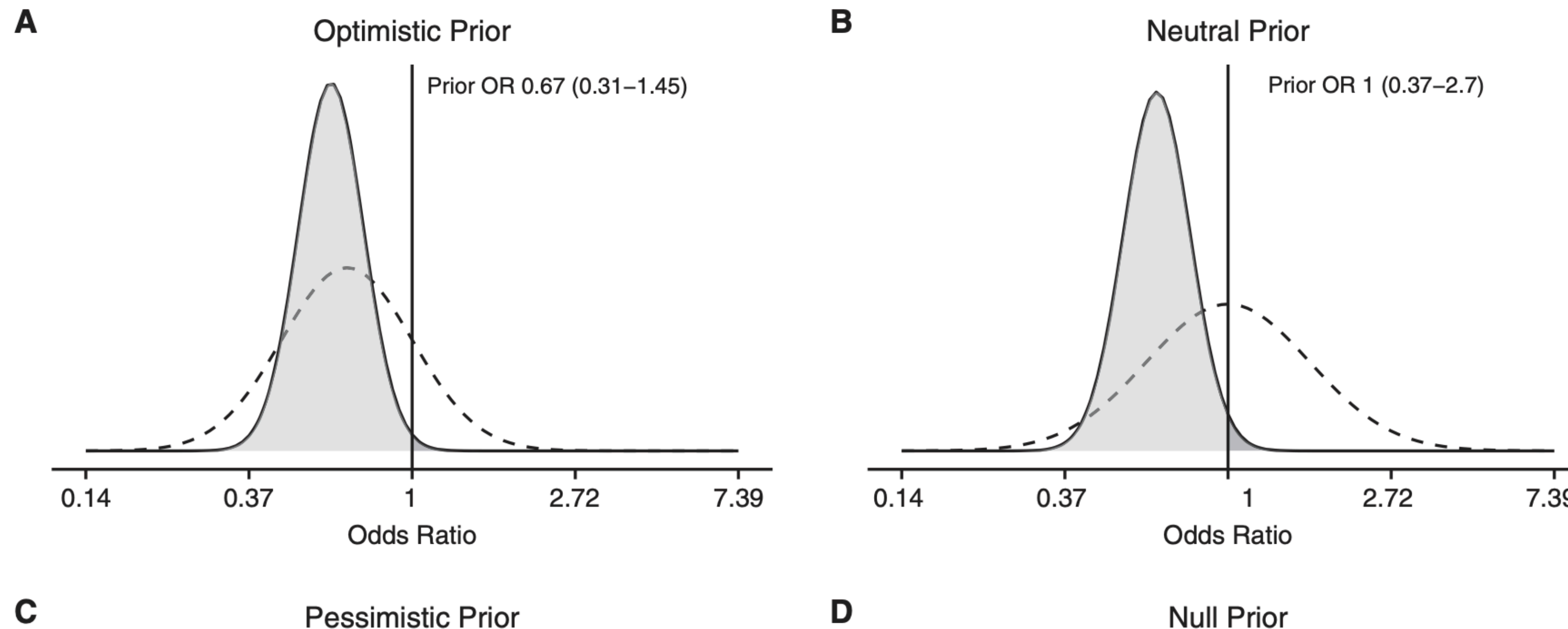


Converting likelihood to probabilities

Zampieri et al 2021 Fig 2

$$\pi(\theta \mid y) = \frac{L(\theta; y)\pi(\theta)}{\int L(\theta; y)\pi(\theta)d\theta}$$

$$\pi_m(\psi \mid y) = \int \pi(\theta \mid y)d\lambda \quad \theta = (\psi, \lambda)$$



2. The discontents

Some challenges

- “The usual regularity conditions”
- High-dimensional parameter space
- Computational intractability
- The model is wrong
- Likelihood is not a probability

Some strategies

- New asymptotic theory
- Other forms of likelihood
- “Likelihood-like” functions
- Semi- and non-parametric approaches
- “Objective” Bayes

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Regularity conditions

Brazzale & Mamelli 2022

224

Journal of the American Statistical Association, March 1985

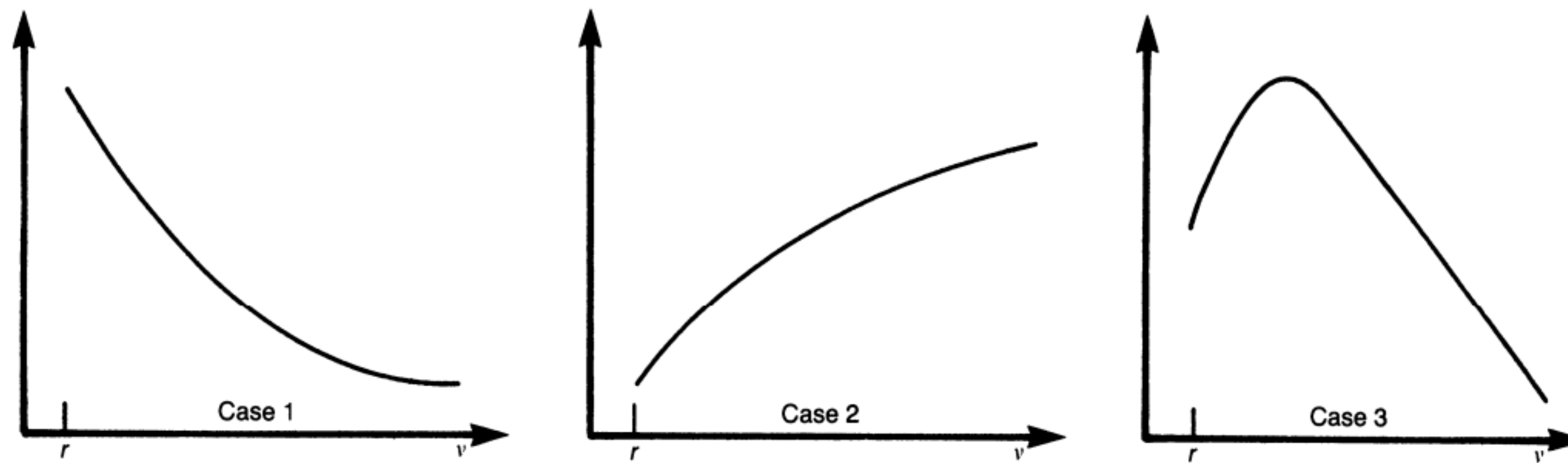


Figure 1. Plots of $g(v | x, r)$.

Joe & R 1985

- Variance component models

$$\sigma_{between}^2 \geq 0$$

- Logistic regression

complete separability: $\hat{\beta} \approx \infty$

- Background + signal

$$Y \sim \text{Poisson}(b + \mu), \quad \mu > 0$$

Regularity: some strategies

- Variance components $\sigma_{between}^2 \geq 0$

New asymptotics — Weighted sum of χ^2

Chernoff 54; Self & Liang 87

- Logistic regression; complete separability; $\hat{\beta} \approx \infty$

Exact conditional likelihood

Cox 58; Mehta & Patel 95

Adjust maximum likelihood equation (de-bias)

Firth 93; Kosmidis & Firth 20

- Background + signal

Significance function seems satisfactory

Fraser Reid Wong 2004

Identifiability

- Mixture models $\pi f(y; \theta_1) + (1 - \pi)f(y; \theta_2)$ Chen & Chen 03, McLachlan et al 2019

If $\pi = 1$, θ not identifiable; if $\theta_1 = \theta_2$, then π not identifiable

- Change-point problems

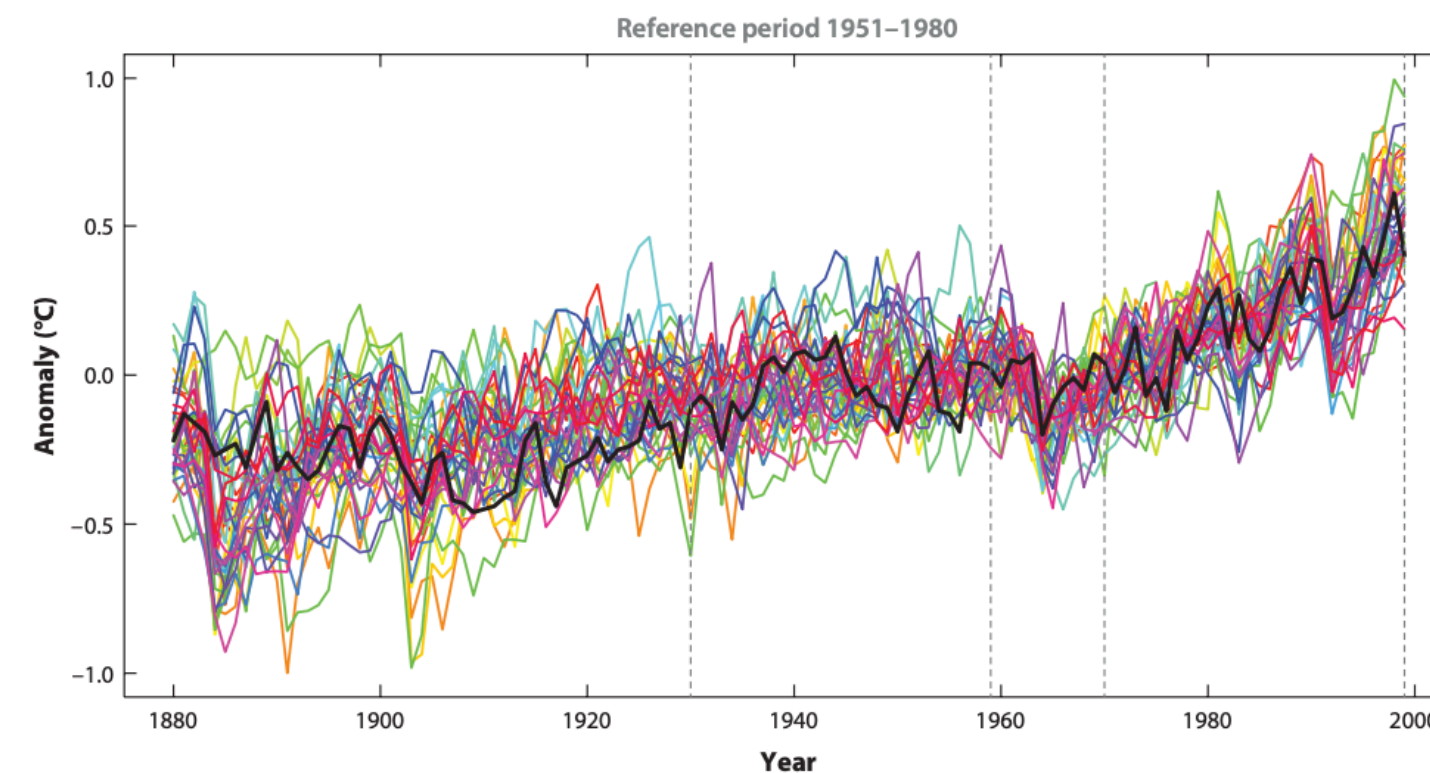


Figure 5
Global average temperature anomalies (*colored paths*) for 1880–1999 relative to the reference period 1951–1980 from 38 models in the Coupled Model Intercomparison Project Phase 5 (CMIP5). The thick black line is the Goddard Institute for Space Studies estimate of global mean temperature. The dashed vertical lines are time periods used in **Figure 6** to compare distributions of models and data.

Guttorp 2014

- New asymptotic arguments; involve maxima of Gaussian processes Cox 2006

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- example: several 2×2 tables with common odds ratio ψ
- $y_{ij} \sim \text{Binom}(m_{ij}; p_i), \quad j = 1, 2; \quad i = 1, \dots, n$
- maximum likelihood estimator not consistent as $n \rightarrow \infty$ if $m_{ij} \equiv 1, \hat{\psi} \rightarrow 2\psi$
- too many nuisance parameters parameter space dimension growing with n

Example:

$$y_{ij} \sim \text{Binom}(m_{ij}, p_{ij}), \quad \text{logit}(p_{ij}) = \psi$$

- conditional likelihood

$f(y_{i1} \mid y_{i1} + y_{i2}; \psi)$ is free of λ

$$\mathbf{L_c}(\psi; \underline{\mathbf{y}}) = \prod_{i=1}^n f(y_{i1} \mid y_{i1} + y_{i2}; \psi) = L_c(\psi; \mathbf{y}_{+1})$$

- Y_{+1} is conditionally sufficient

Fisher's exact test

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Fisher's exact test

- Y_{+1} carries all the information about ψ

“measures ψ ”

- many similar models admit conditional or marginal likelihoods

Battey & Cox, 2020, 22

Many parameters: Likelihood

- we can let number of parameters $\rightarrow \infty$, if we can eliminate nuisance parameters
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Many parameters: Likelihood

- we can let number of parameters $\rightarrow \infty$, if we can eliminate nuisance parameters to create a well-behaved likelihood function matched pairs
- **conditional** and **marginal** likelihood functions can be approximated by adjusting the profile likelihood function $\ell_{prof}(\psi) = \ell(\psi, \hat{\lambda}_{\psi})$

$$\ell_{adj}(\psi) = \ell_{prof}(\psi) - \frac{1}{2} \log |j_{\lambda\lambda}(\psi, \hat{\lambda}_{\psi})| + A(\psi) \quad j_{\lambda\lambda} = -\partial^2 \ell(\psi, \lambda) / \partial \lambda \partial \lambda^T$$

Cox & R 1987

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Cox & R 1987

- $\ell_{adj}(\psi)$ can be converted to a significance function, using higher-order approximations beyond CLT
- but these approximations rely on regularity conditions!, especially fixed dimension

- can let number of parameters increase with n , if nuisance parameters can be eliminated to create a well-behaved likelihood function matched pairs

- but, if $p_n/n \rightarrow \text{constant}$, a new asymptotic theory is needed

$$2\{\ell_{\text{prof}}(\hat{\psi}) - \ell_{\text{prof}}(\psi)\} \xrightarrow{d} \frac{\sigma_*^2}{\lambda_*} \chi_1^2$$

Sur, Chen, Candès 2019

logistic regression, $\psi = \beta_j$

also depends on $\lim_{n \rightarrow \infty} p_n/n$

(σ_*, λ_*) characterized

by studying optimization path

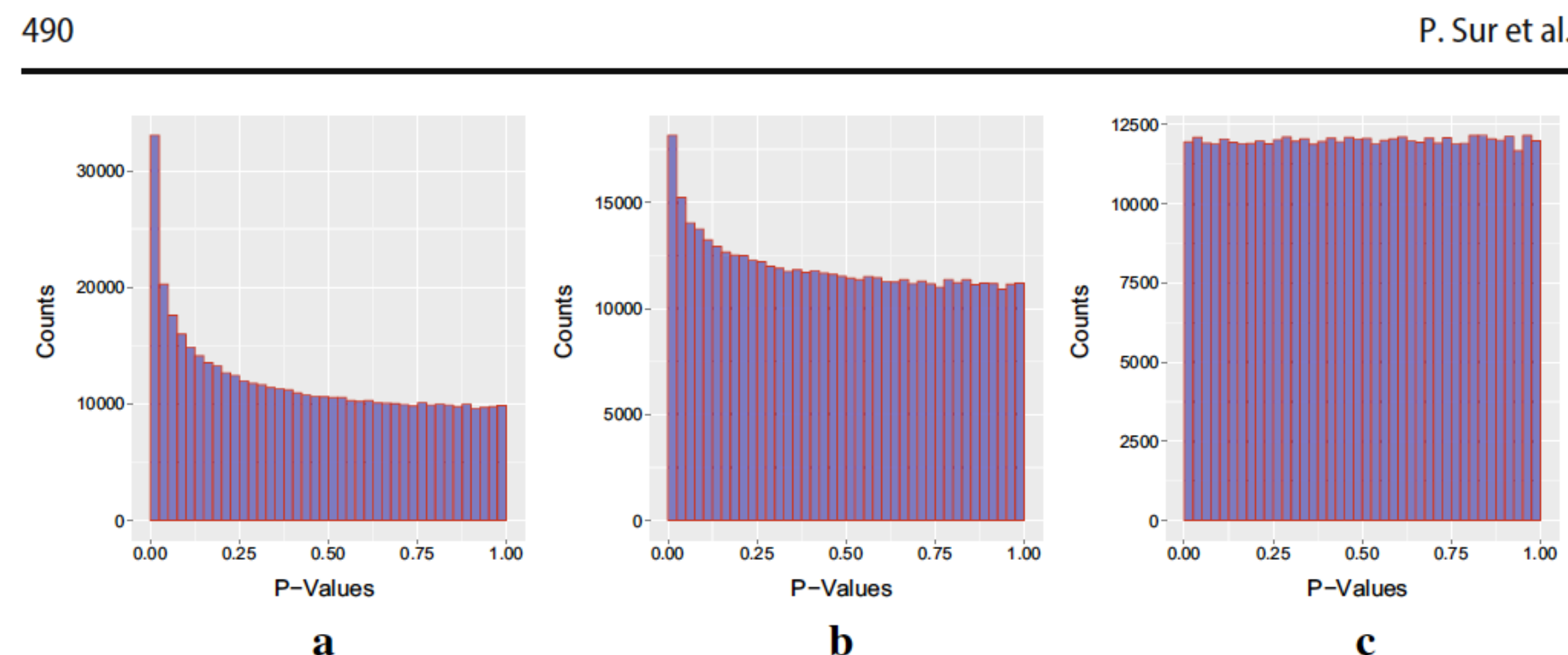


Fig. 1 Histogram of p -values for logistic regression under i.i.d. Gaussian design, when $\beta = \mathbf{0}$, $n = 4000$, $p = 1200$, and $\kappa = 0.3$: **a** classically computed p values; **b** Bartlett corrected p values; **c** adjusted p values

Very many parameters p_n

- in generalized linear models, maximum likelihood estimate not asymptotically normal unless p increases slowly with n
- under $H_0 : \beta = 0$, want p -values based on $(\hat{\beta} - \beta)/\hat{\sigma}_\beta$ to be $U(0, 1)$
- this fails unless $p \sim n^{1/3}$

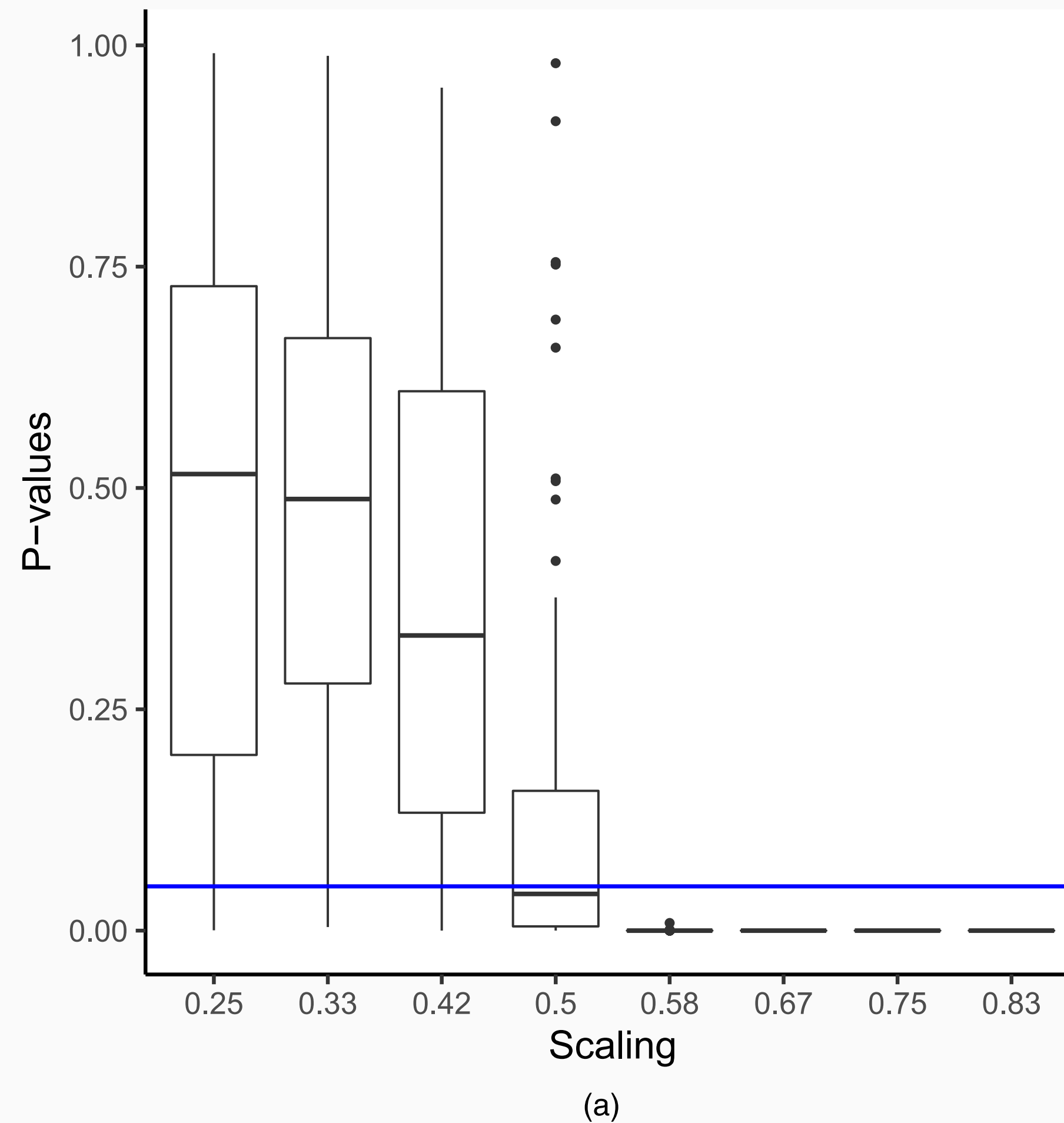
Fan et al 2019

- challenge: theoretical analysis is somewhat specialized
- challenge: estimating σ_β , or σ_*^2/λ_*
- can methods of conditional or marginal likelihood be used for “fairly large” p ?
- shows early promise
- but much work remains

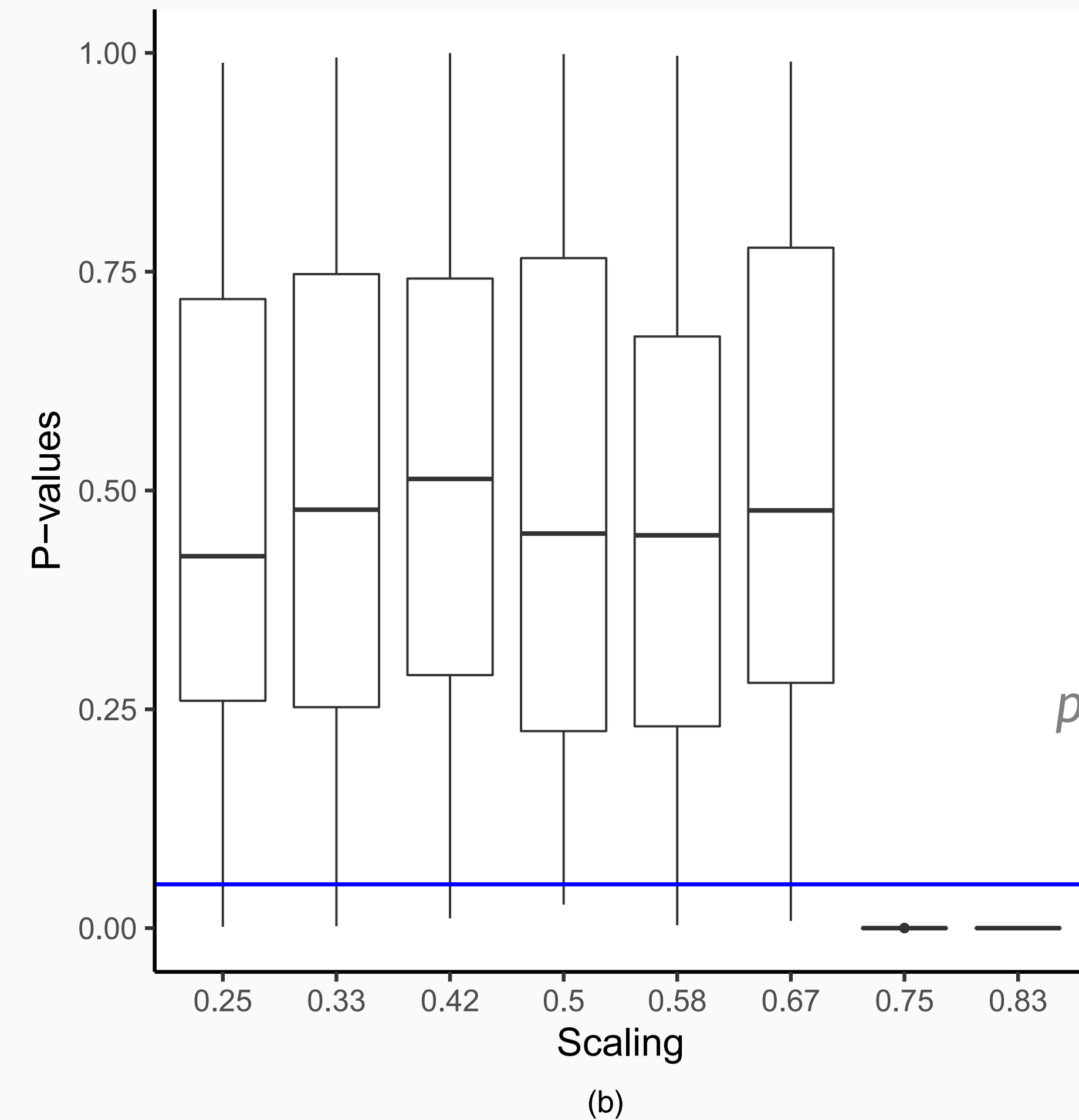
random X ; global null

Tang & R 2020; Lunardon 2019; Battey & R 2022

First-order (normal) approximation



Higher-order approximation



$$p \sim n^{1/3}$$

Fig. 3. Plots for logistic regression illustrating the difference in the breakdown point of uniformity of the p -value distribution based on the standard normal approximation to the distribution of (a) r and of (b) r^* : we see that p -values based on the r^* -approximation appear to be uniformly distributed up to about $p = O(n^{2/3})$, whereas those based on the normal approximation to the distribution of r begin to exhibit non-uniformity at about $p = O(n^{1/2})$.

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The model is wrong

Some strategies:

- **develop new theory** for likelihood inference Cox 1961,2;
- recent example: “Assumption lean inference for generalized linear models”
Vansteelandt & Dukes 2022
- limiting normal distribution for maximum likelihood estimator, but asymptotic
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- **make the model more flexible**
- Example: proportional hazards model $\lambda(y; x, \beta) = \lambda_o(y) \exp(x^T \beta)$ Cox 1972
- justified as a partial likelihood Cox 1975
- can also be interpreted as profile likelihood Murphy & Van der Vaart 2000

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- **go fully nonparametric:** empirical likelihood, constrained density estimation, ...
Balabdaoui et al. 2009; Robeva et al. 2021

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The likelihood function is intractable

- example: latent Gaussian model

Rue et al. 2017

$$f(y \mid z; \theta) = \prod_{i \in \mathcal{I}} f(y_i \mid z_i; \theta), \quad z \sim N\{\mu(\tau), \Sigma(\tau)\}$$

$$L(\theta; y) = \int f(y \mid z; \theta) f(z; \tau) \pi(\tau) dz d\tau$$

- spatial processes, network models, multivariate extremes, **agent-based models**
- one strategy: **composite likelihood**
- replace $L(\theta; \underline{y}) \propto f(\underline{y}; \theta)$ by, e.g.,

pseudo-likelihood

$$cL(\theta; \underline{y}) = \prod_{j < k} f_2(y_j, y_k; \theta)$$

- a type of wrong model, with some nice properties
- asymptotic theory has been developed as on previous slide

Molenberghs & Verbeke, 2005; Lindsay, 1988

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objective, weakly informative
- posterior may give inference methods with good performance under the model
calibrated inference
- this needs to be checked in each application

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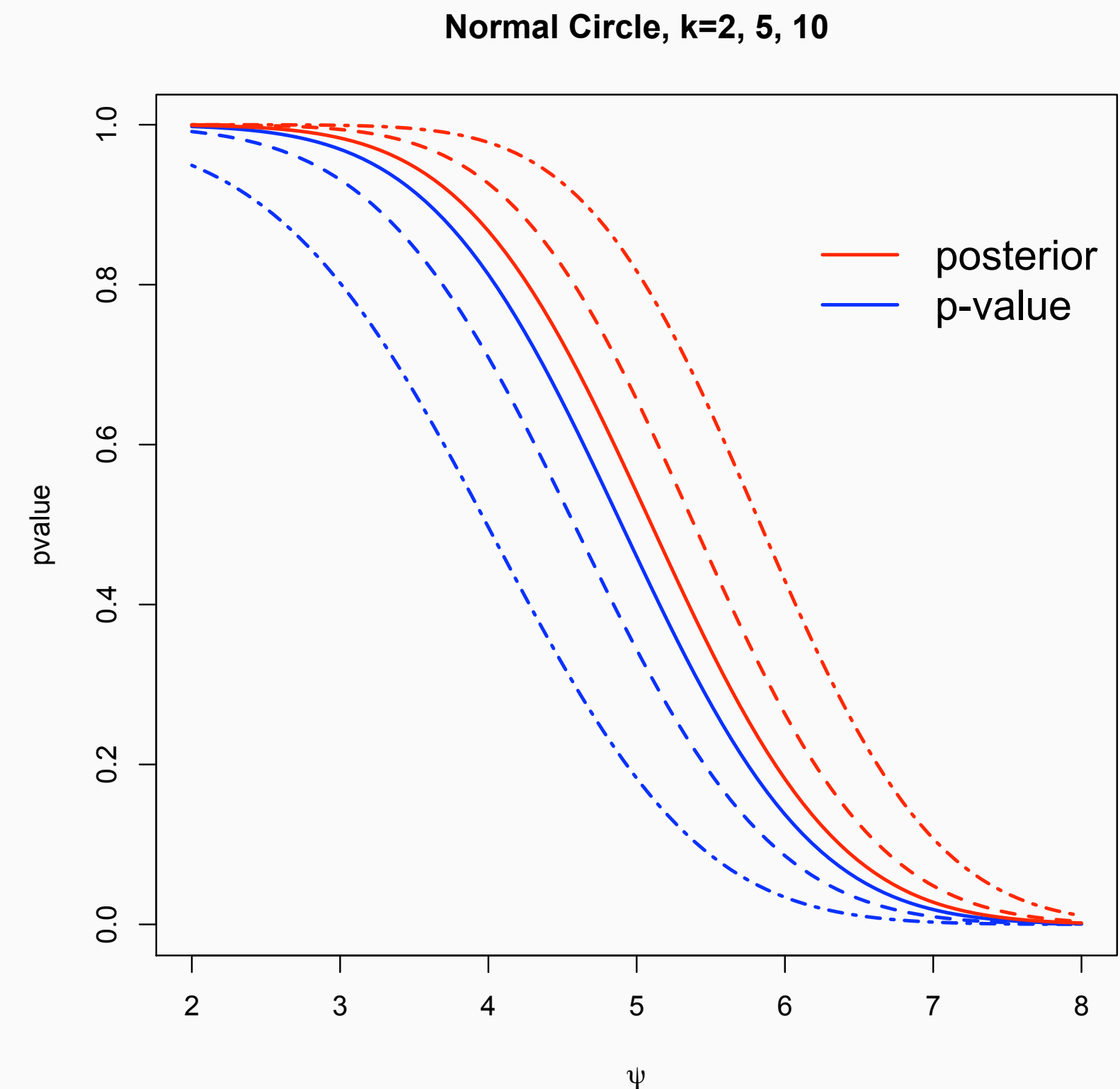
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- satellite conjunction analysis
Elkantassi & Davison 2022
- inference for length of a normal vector
Stein 1959

- $y_i \sim N(\theta_i, 1/\textcolor{red}{n}), \quad i = 1, \dots, \textcolor{blue}{k}; \quad \pi(\underline{\theta}) \propto 1$
- posterior distribution of $a^\top \theta$ is well-calibrated
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- a toy example? Yes, but has recently re-emerged

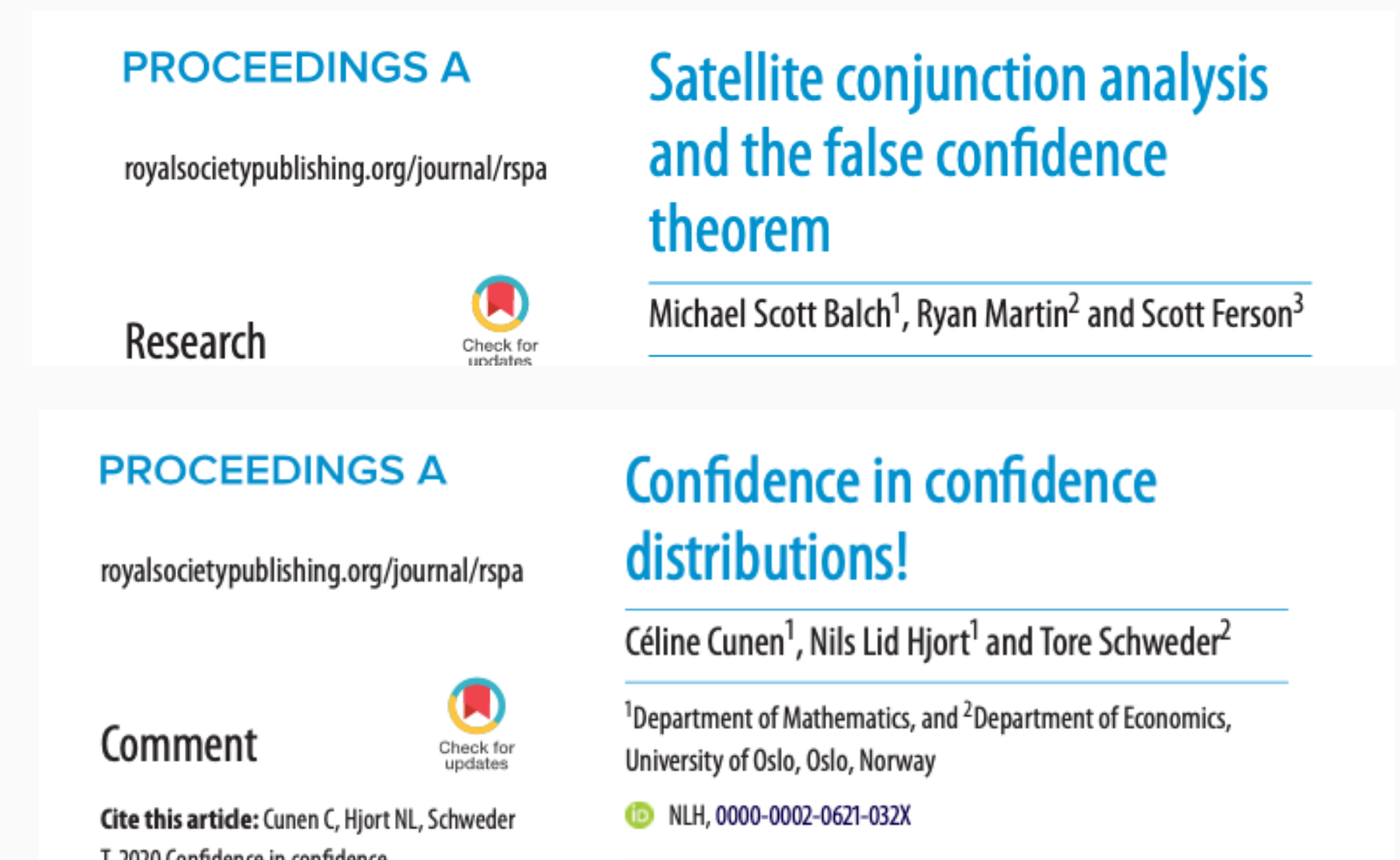
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Satellite conjunction analysis

- estimating probability of satellites passing too close to each other collision risk
- simplified version requires estimation of length of a normal vector

- Bayesian version highlighted in Balch et al.



- response by Cunen et al.
- detailed treatment in Elkantassi & Davison 2022

J Guidance Control and Dynamics

further response by Balch et al. to Cunen on interpretation of confidence distributions

So much detail!

- Many adjective-likelihood functions

Marginal, conditional, partial, composite, pseudo

Quasi, empirical, bootstrap, simulated, sieve, penalized

- Common theme: provide inference strategies with well-understood properties
- Enables us to move away from the specific problem at hand
- Theory provides guidance for a range of similar applications

3. Theory and Applications

Statistics in the news

Economist, July 29



≡ Menu

Weekly edition

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Science & technology | Nudge factor

Evidence for behavioural interventions looks increasingly shaky

The academic literature is plagued by publication bias

“plagued by publication bias”





RESEARCH ARTICLE | PSYCHOLOGICAL AND COGNITIVE SCIENCES | 



The effectiveness of nudging: A meta-analysis of choice architecture interventions across behavioral domains

[Stephanie Mertens](#)  , [Mario Herberz](#) , [Ulf J. J. Hahnel](#) , and [Tobias Brosch](#)   [Authors Info & Affiliations](#)

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THIS ARTICLE HAS BEEN UPDATED

The response

LETTER | JULY 19, 2022 | 

No reason to expect large and consistent effects of nudge interventions

Barnabas Szaszi, Anthony Higney, [...] Elizabeth Tipton



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The effectiveness of nudging: A meta-analysis of choice architecture interventions across behavioral domains

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Reply to Maier et al., Szaszi et al., and Bakdash and Marusich: The present and future of choice architecture research

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No evidence for nudging after adjusting for publication bias

Maximilian Maier, František Bartoš, [...] Eric-Jan Wagenmakers



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Left-truncated effects and overestimated meta-analytic means

Jonathan Z. Bakdash and Laura R. Marusich



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Reply to Maier et al., Szaszi et al., and Bakdash and Marusich: The present and future of choice architecture research

Stephanie Mertens, Mario Herberz, [...] Tobias Brosch




[THIS ARTICLE REPLIES TO:](#)

No evidence for nudging after adjusting for publication bias

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No reason to expect large and consistent effects of nudge interventions

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The effectiveness of nudging: A meta-analysis of choice architecture interventions across behavioral domains

Contributors: [Stephanie Mertens](#), [Mario Herberz](#), [Ulf J.J. Hahnel](#), [Tobias Brosch](#)

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Description: *This project is funded by the Swiss National Science Foundation and the Swiss Federal Office of Energy. It investigates the effectiveness of choice architecture interventions across behavioral domains.*

Files

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Citation

Components

Some details

Mertens et al. 2021

“Materials and methods”

- 440 estimates of effect size: $(\text{treatment} - \text{control mean}) / (\text{estimated std error})$
- 212 unique publications; sometimes several tmts with the same control
- Random effects to accommodate this
- Additional fixed effects (moderators) for secondary analysis —
types of interventions; behavioural domain; study characteristics
- Publication bias assessed by plotting standard error vs effect size Egger's test

Some results

Mertens et al. 2021

Figure 2

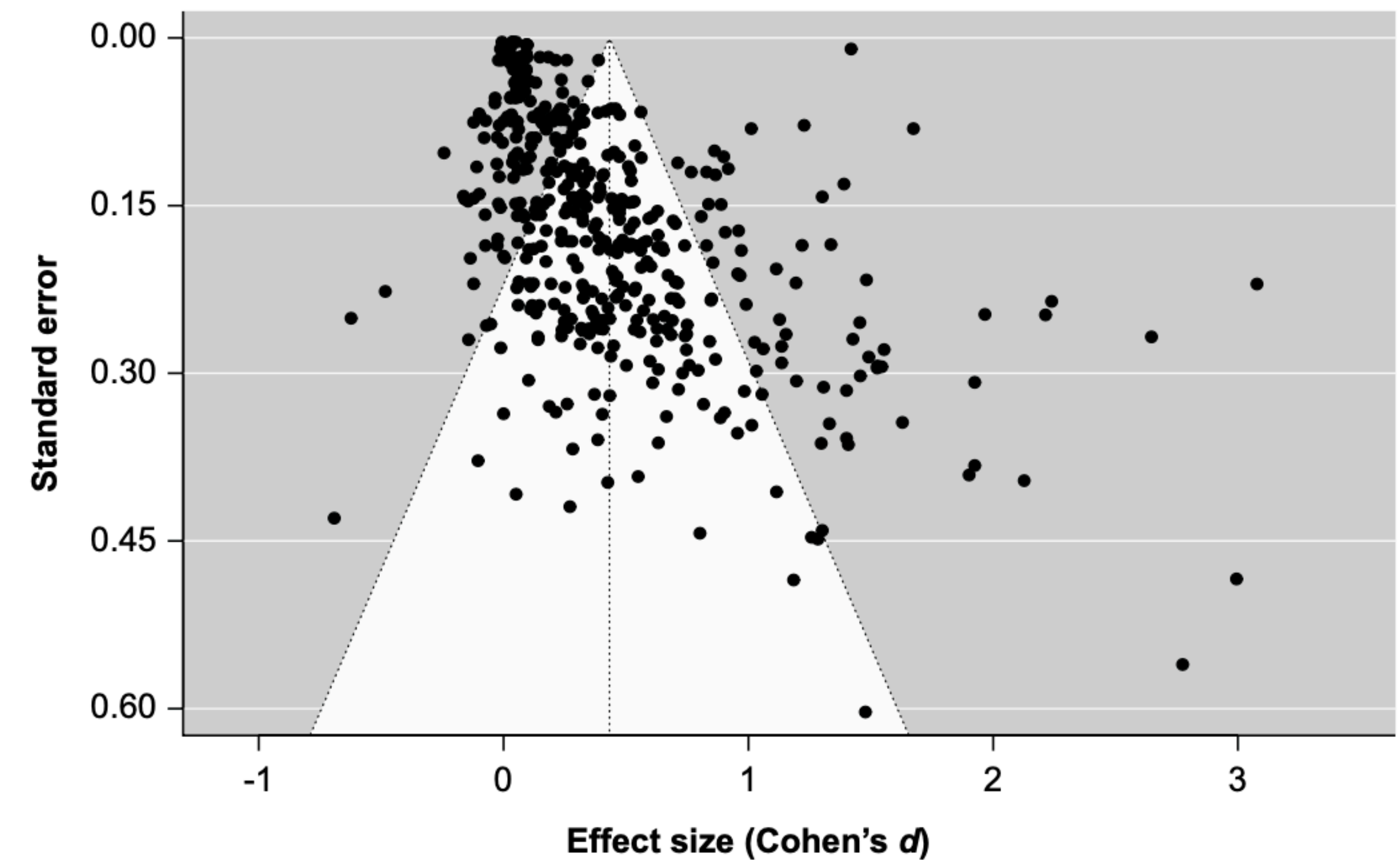
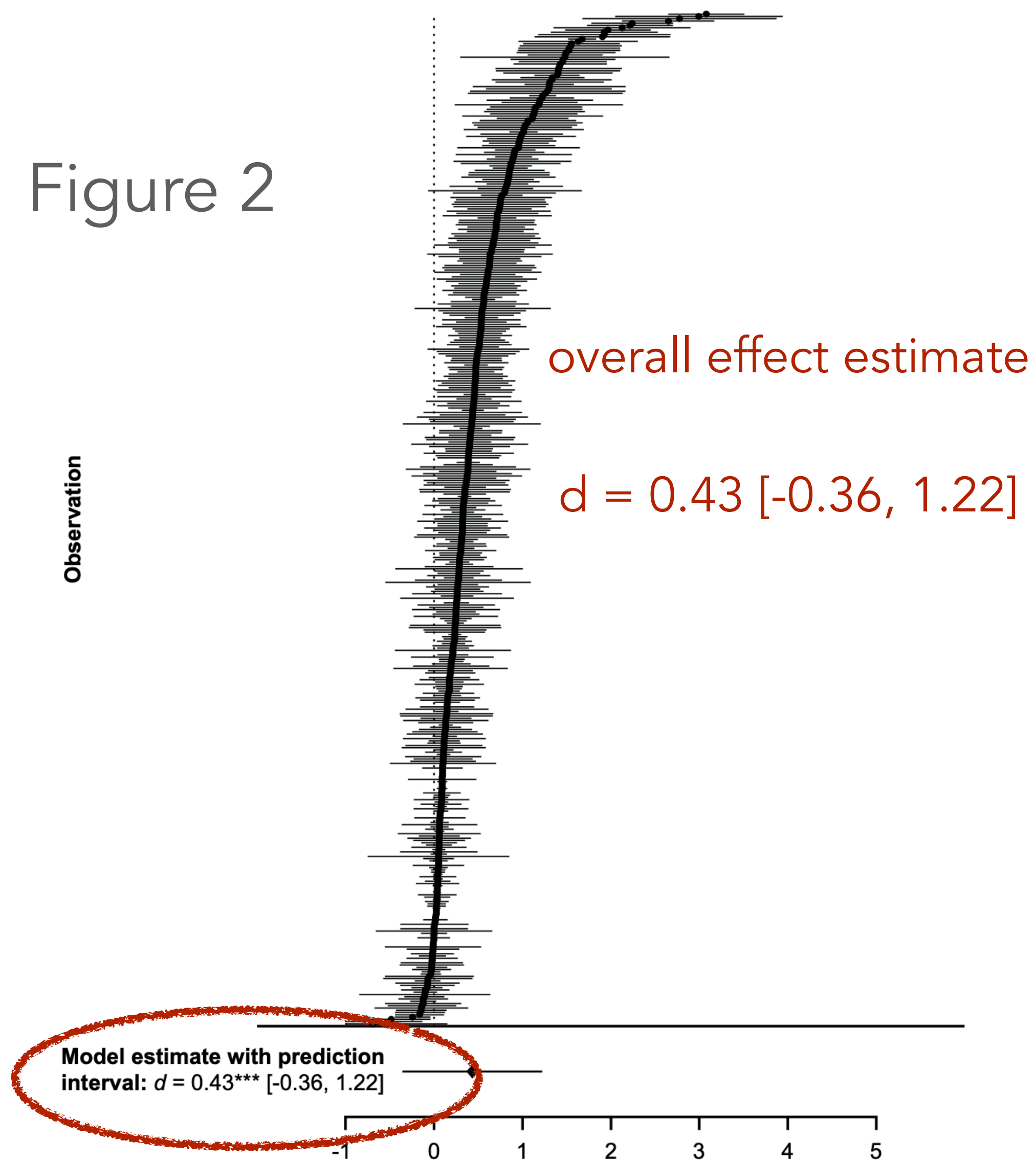


Fig. 3. Funnel plot displaying each observation as a function of its effect size and SE. In the absence of publication bias, observations should scatter

Standard error increases with effect size

The letters

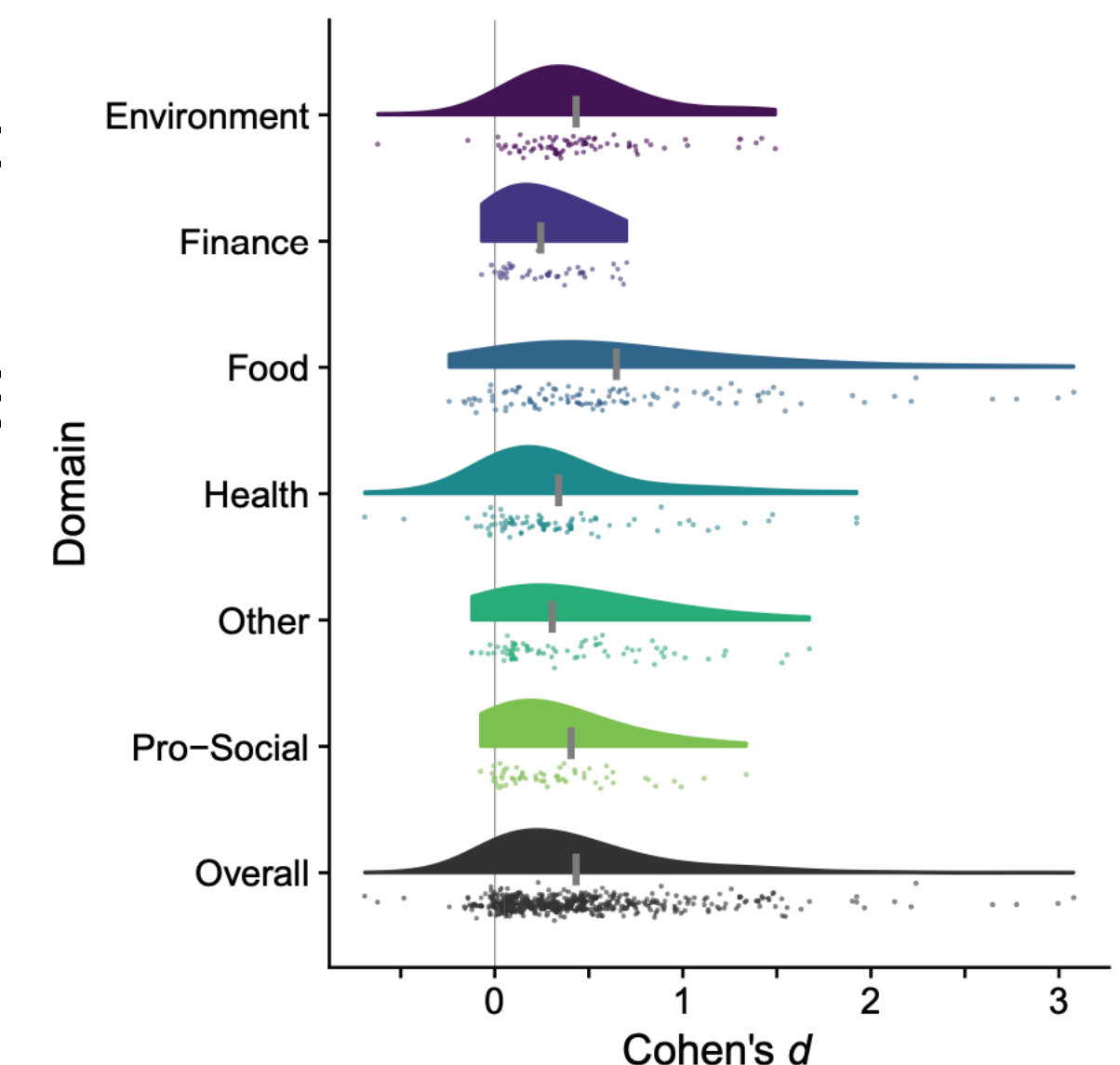
1. Maier et al. — publication bias not correctly taken into consideration

“A newly-proposed bias-correction technique — robust Bayesian meta-analysis avoids an ‘all-or-none’ debate over whether or not publication bias is ‘severe’ ”

2. Szaszi et al. — the average effect size is not very informative, given the variation between studies

“Even after adjusting for publication bias, the effects ... vary considerably

3. Bakdash & Maurisch — estimated effects in studies are right-skewed

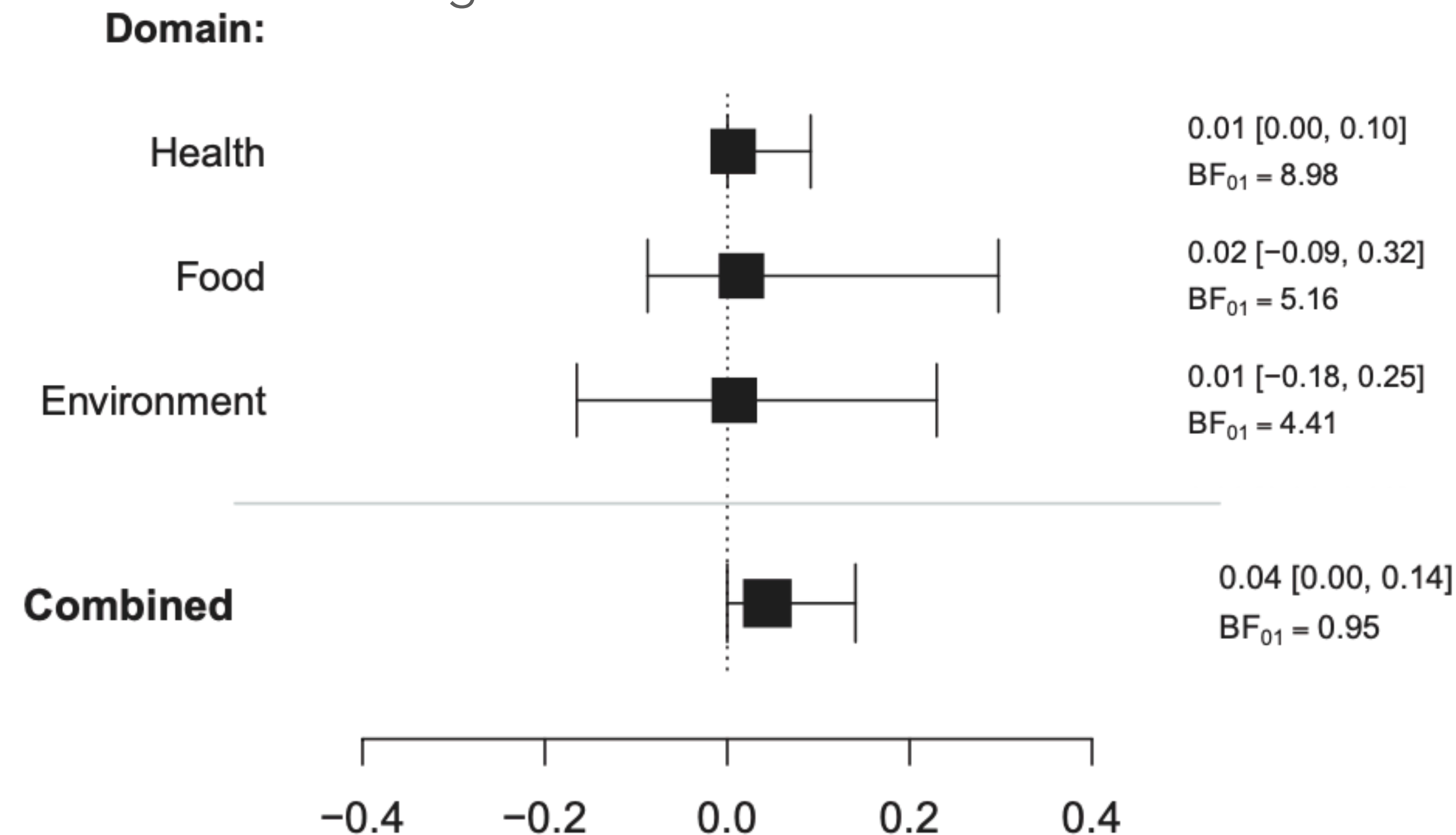


Foundations

1. Maier et al. — publication bias not correctly taken into consideration

“A newly-proposed bias-correction technique — robust Bayesian meta-analysis avoids an ‘all-or-none’ debate over whether or not publication bias is ‘severe’ ”

Figure 1 Meier et al.



Model-averaged mean effect size estimates with posterior credibility intervals and Bayes factors

Szaszi et al applied various non-Bayesian adjustments for bias with similar results

Science and sports

Borg et al. 2022

Outside

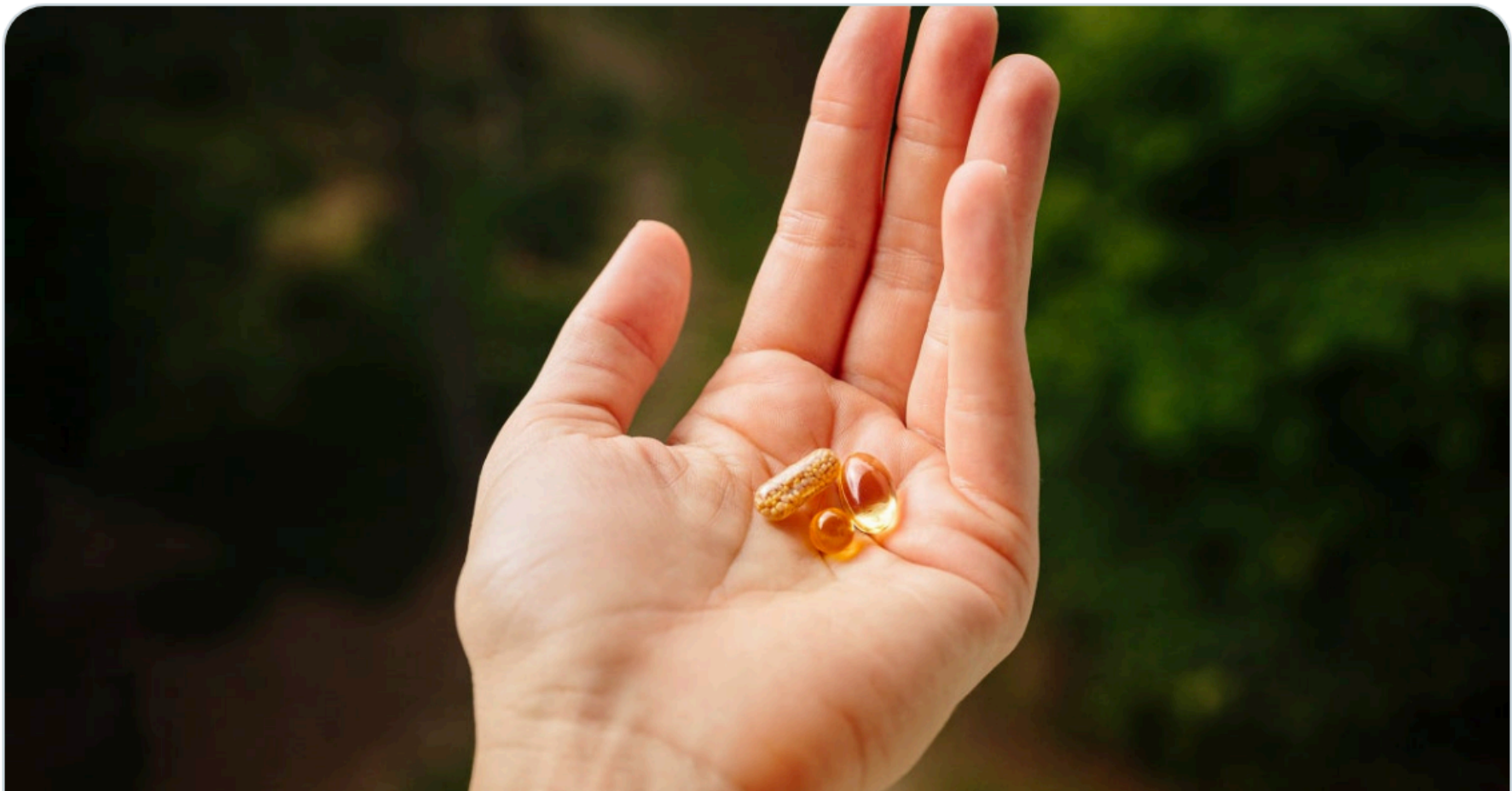
Why That New “Science-Backed” Supplement Probably Doesn’t Work

A deep dive into the sports science literature shows why you should be wary of results that seem too good to be true

← Tweet




"the journal Science and Medicine in Football, for example, introduced registered reports three years ago but has yet to receive a single submission."



outsideonline.com

Why That New “Science-Backed” Supplement Probably Doesn’t Work
A deep dive into the sports science literature shows why you should be wary of results that seem too good to be true

8:57 PM · Aug 4, 2022 · Twitter Web App

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The Bias for Statistical Significance in Sport and Exercise Medicine

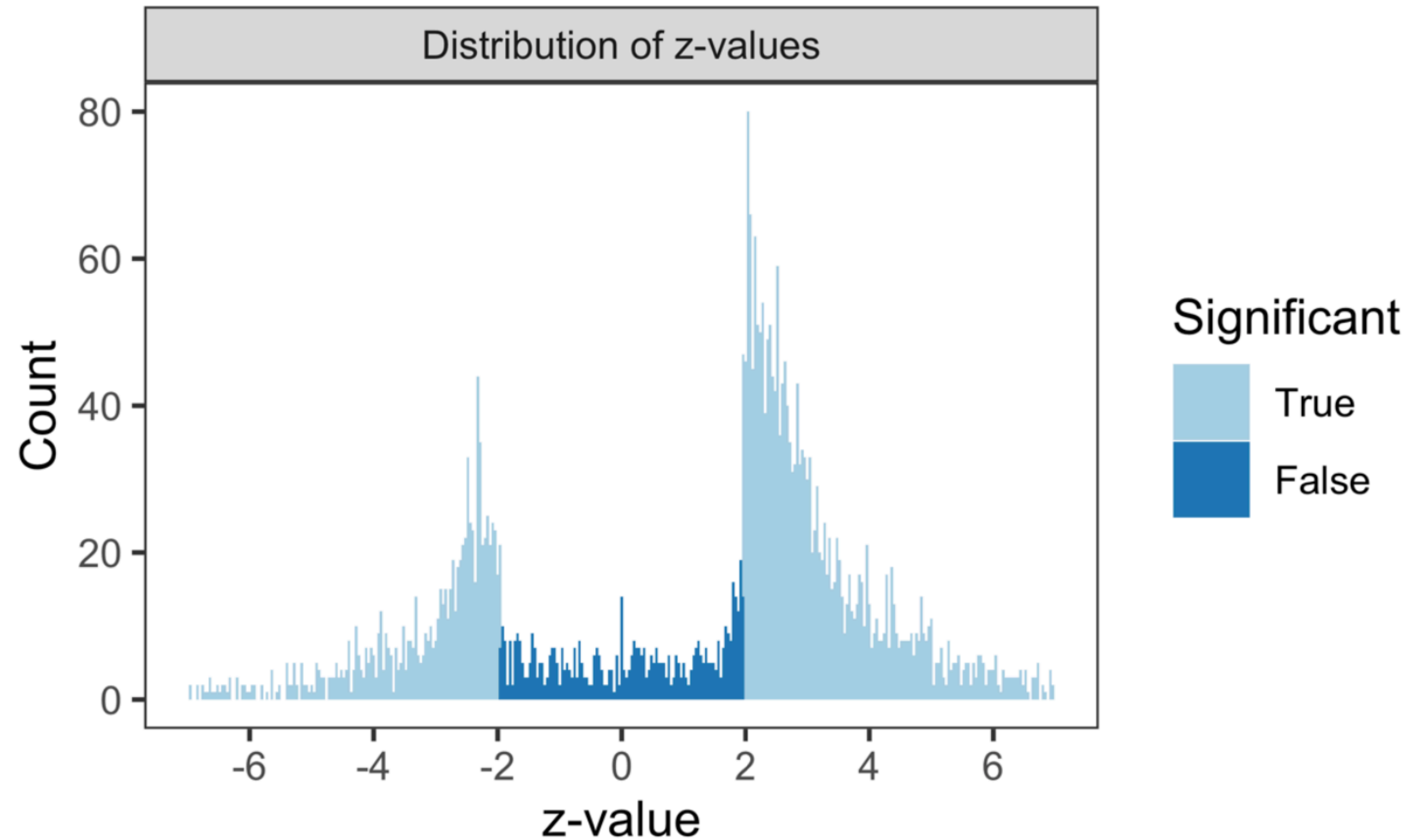
AUTHORS
David N Borg, Adrian Barnett, Aaron R Caldwell, Nicole White, Ian Stewart

AUTHOR ASSERTIONS

Conflict of Interest: Yes ▼Public Data: Available ▼Preregistration: No ▼

The missing middle

Borg et al. Figure 3



Another nudge



A dynamic message sign displays traffic deaths above the H-1 Freeway on the Liliha Street overpass in Hawaii.

BEHAVIORAL SCIENCE

How safe are safety messages?

Highway fatalities increased in response to certain messages

Science

Ullman & Chrysler 2022

- "... research by Hall and Madsen suggests that, contrary to expectations, displaying traffic fatality numbers in traffic safety messages is associated with an increase in fatalities downstream"
- "... seems inconsistent with other research that has found ... mostly ineffective"
- "... the issue may be one of excessive salience or cognitive overload"

A natural experiment

Science April 22 2022

RESEARCH

RESEARCH ARTICLE

TRAFFIC SAFETY

Can behavioral interventions be too salient? Evidence from traffic safety messages

Jonathan D. Hall^{1,2} and Joshua M. Madsen^{3*}

	Crashes per hour (%)		
	3 km	5 km	10 km
	(1)	(2)	(3)
Campaign week × post	1.13 (0.86)	1.52 (0.68)**	1.35 (0.60)**
Campaign week	0.35 (0.63)	−0.27 (0.48)	−0.32 (0.43)
Observations	61,697,666	61,697,666	61,697,666
Adjusted R^2	0.02	0.03	0.08
Rain and interactions	Yes	Yes	Yes
S-Y-M-D-H FE	Yes	Yes	Yes
Holiday FE	Yes	Yes	Yes

Hall & Madsen 2022

- data from Texas; messages about fatalities posted 1 week of four
- researchers were able to use the other weeks as “controls”
- with adjustments for weather, time of day, etc.,
- concluded that accidents increased by roughly 1.5% in weeks when messages displayed
- small but “statistically significant”
?

Diet and health

NY Times July 12 2022



The New York Times

Account ▾

ASK WELL

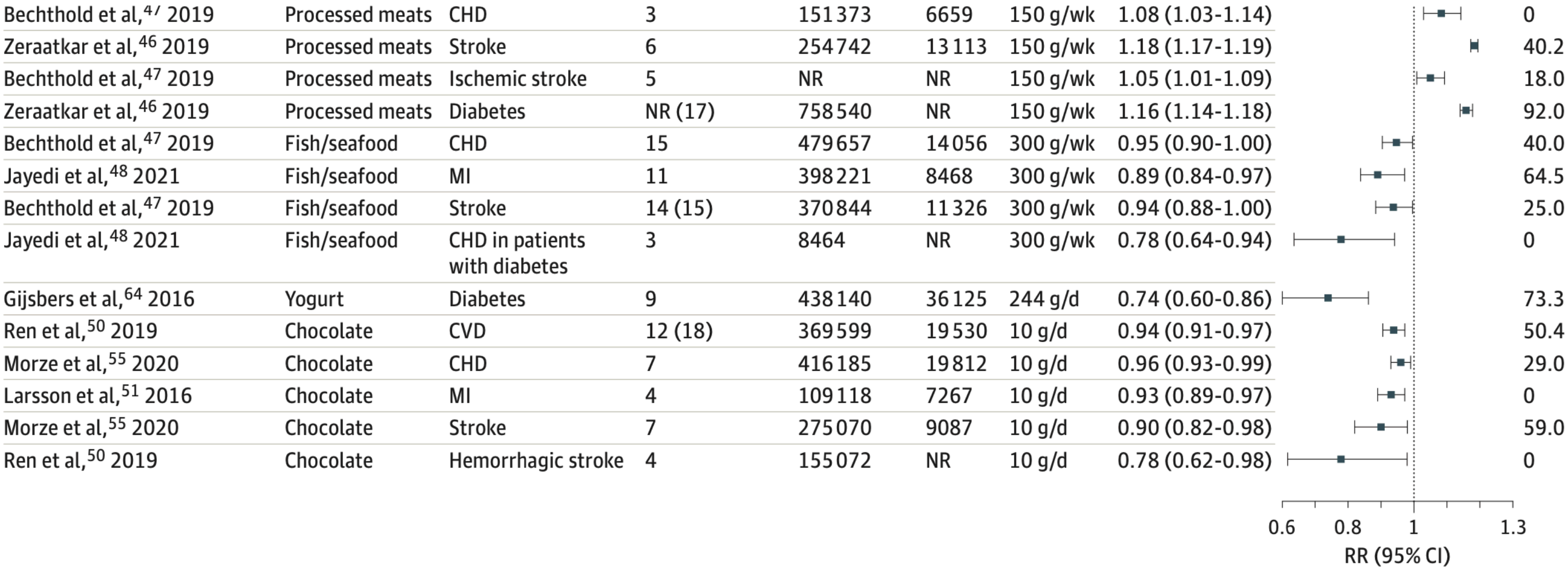
Is Chocolate Good for You?

Studies suggest that cocoa might benefit health, but it's unclear how that may translate to a typical bar of chocolate.



- refers to:
- a review of several (small) meta-analyses Miller et al 2022
- a large randomized trial Sessa et al 2022

ASK WELL
Is Chocolate Good for You?
Studies suggest that cocoa might benefit health, but it's unclear how that may translate to a typical bar of chocolate.



The COSMOS trial

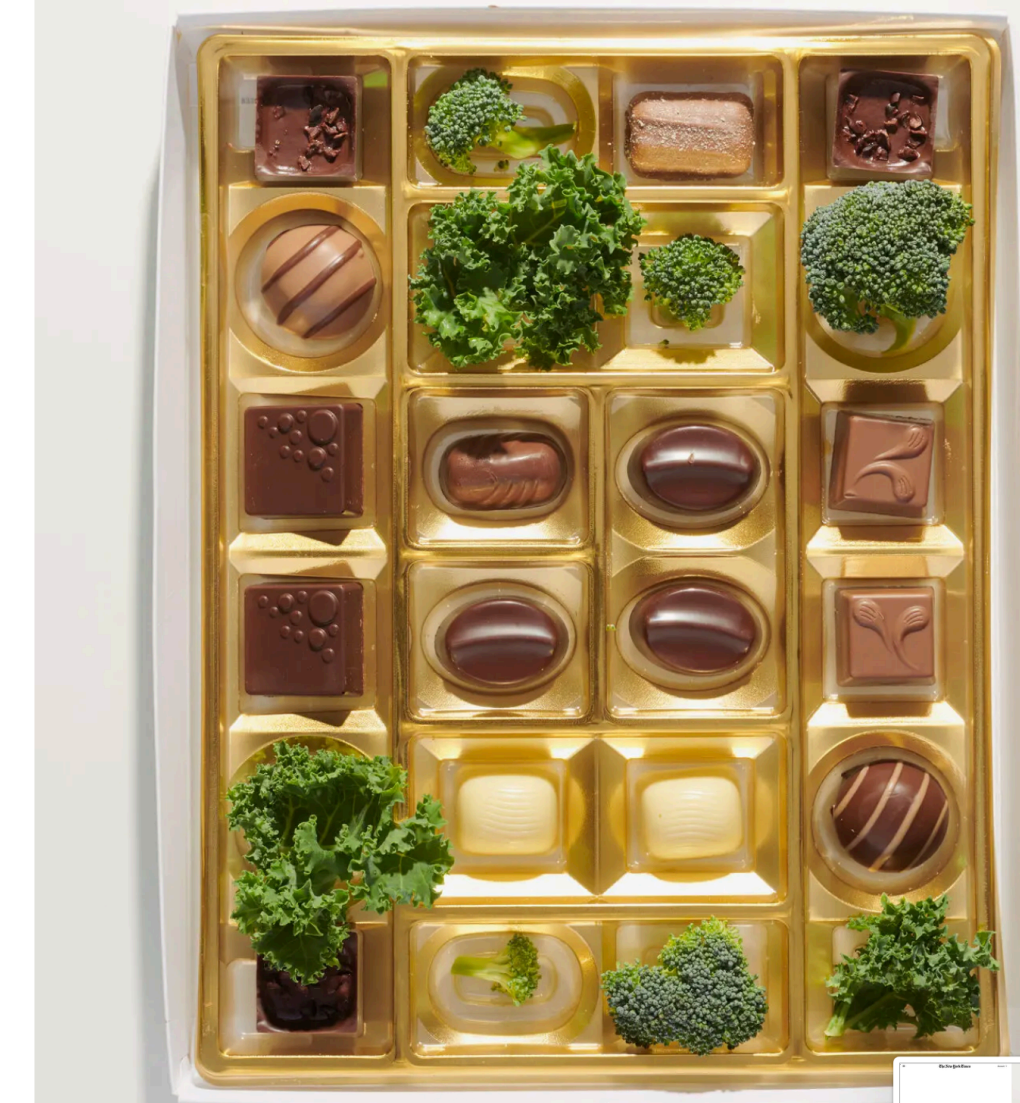
Sessa et al. 2022

- randomized, double-blind, placebo controlled trial
- 21,442 US adults (convenience sample)
- tested a cocoa extract supplement (not chocolate)
- limitations carefully noted in discussion
- “there was no statistically significant effect on the primary outcome”
- “however, cocoa ... significantly reduced CVD death by 27%

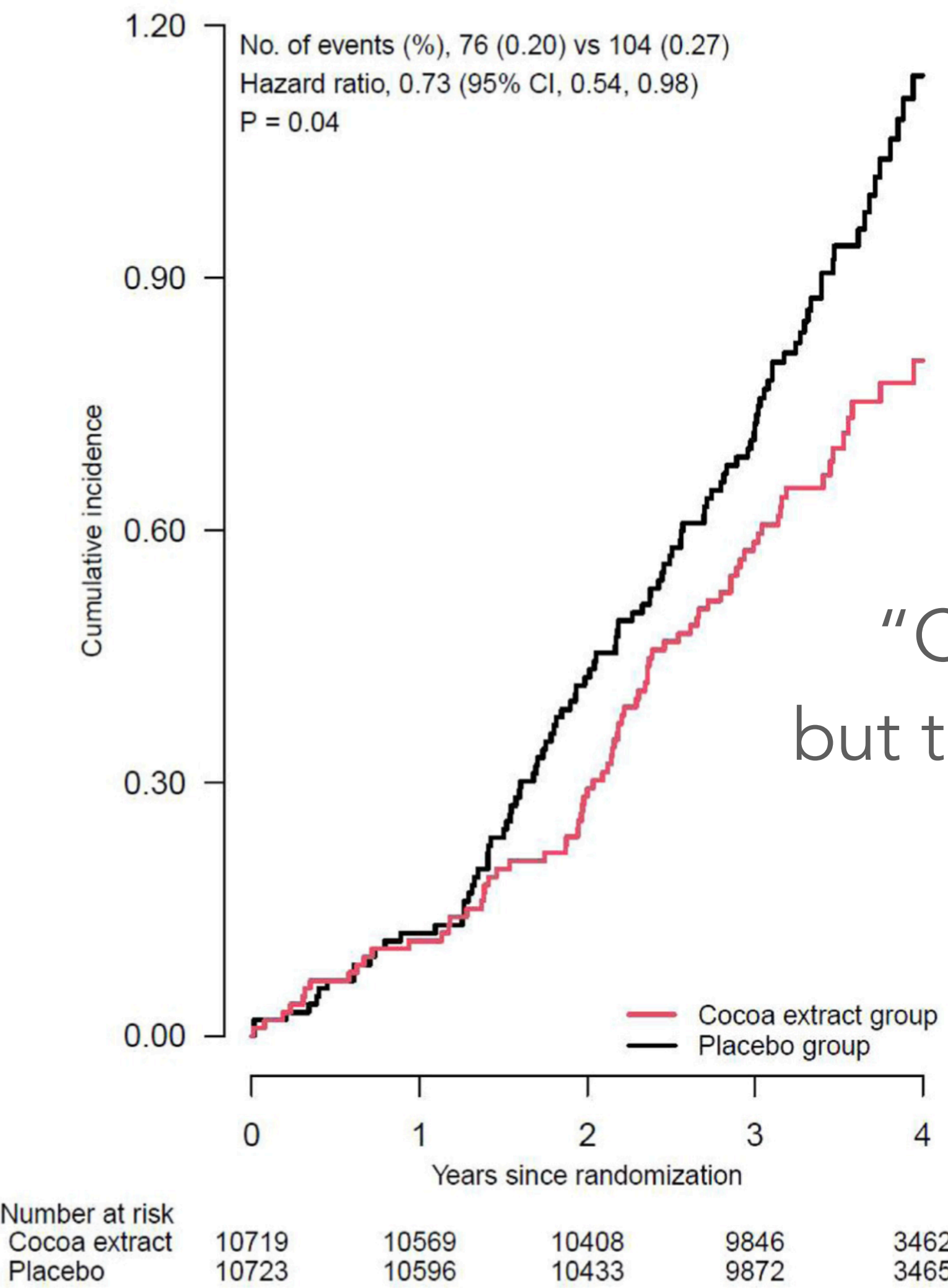
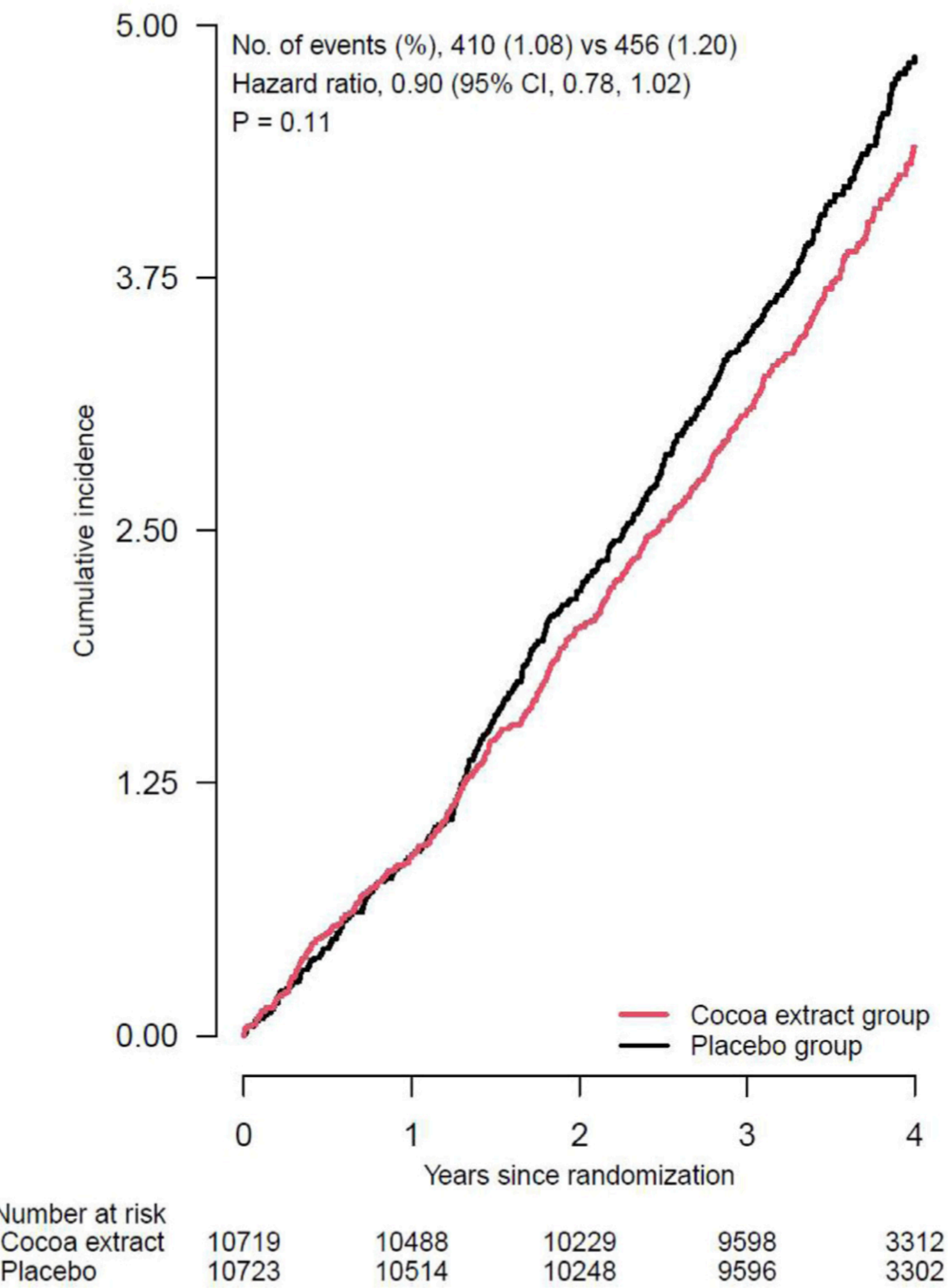
ASK WELL

Is Chocolate Good for You?

Studies suggest that cocoa might benefit health, but it's unclear how that may translate to a typical bar of chocolate.



The COSMOS trial



“Chocolate is a wonderful treat,
but to perceive it as a health food,
I think it has its limitations”

Some stories never die

March 2010

“Researchers find those who eat 7.5 grams a day have a lower risk of heart disease”

August 2005

An ounce of (dark chocolate) prevention


Or less: Researchers find those who eat 7.5 grams a day have a lower risk of heart disease

BY KATE KELLAND

Easter eggs may be good for you, but only if you eat small ones made from cocoa-rich dark chocolate, according to the latest in a string of scientific studies to show potential health benefits of chocolate.

German researchers studied more than 19,300 people over a decade and found those who ate the most chocolate – an average of 7.5 grams a day – had lower blood pressure and a 39 per cent lower risk of having a heart attack or stroke than those who ate the least amount of chocolate – an average of 1.7 grams a day.

But the difference between the two groups was just less than six grams of chocolate a day, less than one small square of an average 100-gram bar, they wrote in a study in the European Heart Journal to be published today.




Good for heart health. ELISE AMENDOLA/ASSOCIATED PRESS

ONTARIO EDITION • TORONTO WEATHER: AFTERNOON THUNDERSHOWERS, HIGH 32. MAP AND DETAILS, S8

Can chocolate save your life?

EATING JUST THE RIGHT KIND CAN HELP WARD OFF DISEASE, LESLIE BECK WRITES. A11

S&P/TSX COMPOSITE 10,58



Why condoms are sizz

... and weight were details of their health were of absolute risk, dings showed in the group eat- nount of choco- their chocolate rams a day, 85 acks and strokes o people could occur over a pe- o years. on the study on european Society

Hospital Zurich said basic science had now demonstrated “quite convincingly” that dark chocolate with a cocoa content of at least 70 per cent reduces some kinds of stress and can improve blood flow and blood pressure. But he said: “Before you rush to add dark chocolate to your diet, be aware that 100 grams ... contains roughly 500 calories. “You may want to subtract an equivalent amount of calories by cutting back on other foods

Statistics in science and society

- Haphazard examples from hundreds of similar stories
- P-values are everywhere
- But statistical issues of sampling, bias, reproducibility, etc. much more prominent
- For example:

New Online Views 0 | Citations 0 | Altmetric 2

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JAMA Guide to Statistics and Methods ONLINE FIRST FREE

August 4, 2022

Regression Models for Ordinal Outcomes

Benjamin French, PhD^{1,2}; Matthew S. Shotwell, PhD¹

» Author Affiliations | Article Information

JAMA. Published online August 4, 2022. doi:10.1001/jama.2022.12104

nature methods

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This Month | **Published: 04 August 2022**

POINTS OF SIGNIFICANCE

Survival analysis—time-to-event data and censoring

Tanujit Dey, Stuart R. Lipsitz, Zara Cooper, Quoc-Dien Trinh, Martin Krzywinski & Naomi Altman

Nature Methods 19, 906–908 (2022) | [Cite this article](#)

404 Accesses | 4 Altmetric | [Metrics](#)

Statistics in data science

Kapoor & Narayanan

Leakage and the Reproducibility Crisis in ML-based Science

We argue that there is a reproducibility crisis in ML-based science. We compile evidence of this crisis across fields, identify data leakage as a pervasive cause of reproducibility failures, conduct our own reproducibility investigations using in-depth code-review, and propose a solution.



[Draft paper](#)

[July 28 online workshop](#)

- blog post emphasizes data leakage — overlap between train and test sets, features proxy for outcome, test set has different distribution
- “There is a much better known reproducibility crisis in research that uses traditional statistical methods.”

Thanks are due



Christian Genest



Erica Moodie



Heather Battey



Yanbo Tang

It's the friends you make



THANK YOU

