

Preclinical Study Design Considerations

Don't be a bias denier

Anton Bespalov, MD, DMedSci

*Partnership for Assessment and Accreditation of Scientific Practice
Heidelberg, Germany*

Thomas Hudzik, PhD

ALA+ BioPharma Consulting

Disclosures

Anton Bespalov is Co-founder and managing partner at PAASP GmbH, a Shareholder at PAASP US LLC, Co-founder and CSO / managing director at EXCIVA GmbH

Thomas Hudzik is a consultant for pharma, NIDA, biomedical research institutions, World Anti-Doping

Outline

- Definition of a 'good' study design
- Blinding
- Randomization
- The power and peril of pre-specification of endpoints

Recommended (re)Reading

Why Most Published Research Findings Are False

John P. A. Ioannidis

PLoS Medicine August 2005 | Volume 2 | Issue 8 | e124

Elements of Good Study Design

- ‘Good’ Definition: data output
 - High validity, fidelity, replicability
- Achieved by study design that minimizes bias, maximizes rigor
 - Powering, **blinding, randomization**, use of appropriate controls, training, statistics, record-keeping, use of positive controls and comparators, **pre-specification (endpoints, comparisons made, etc)**

Outline

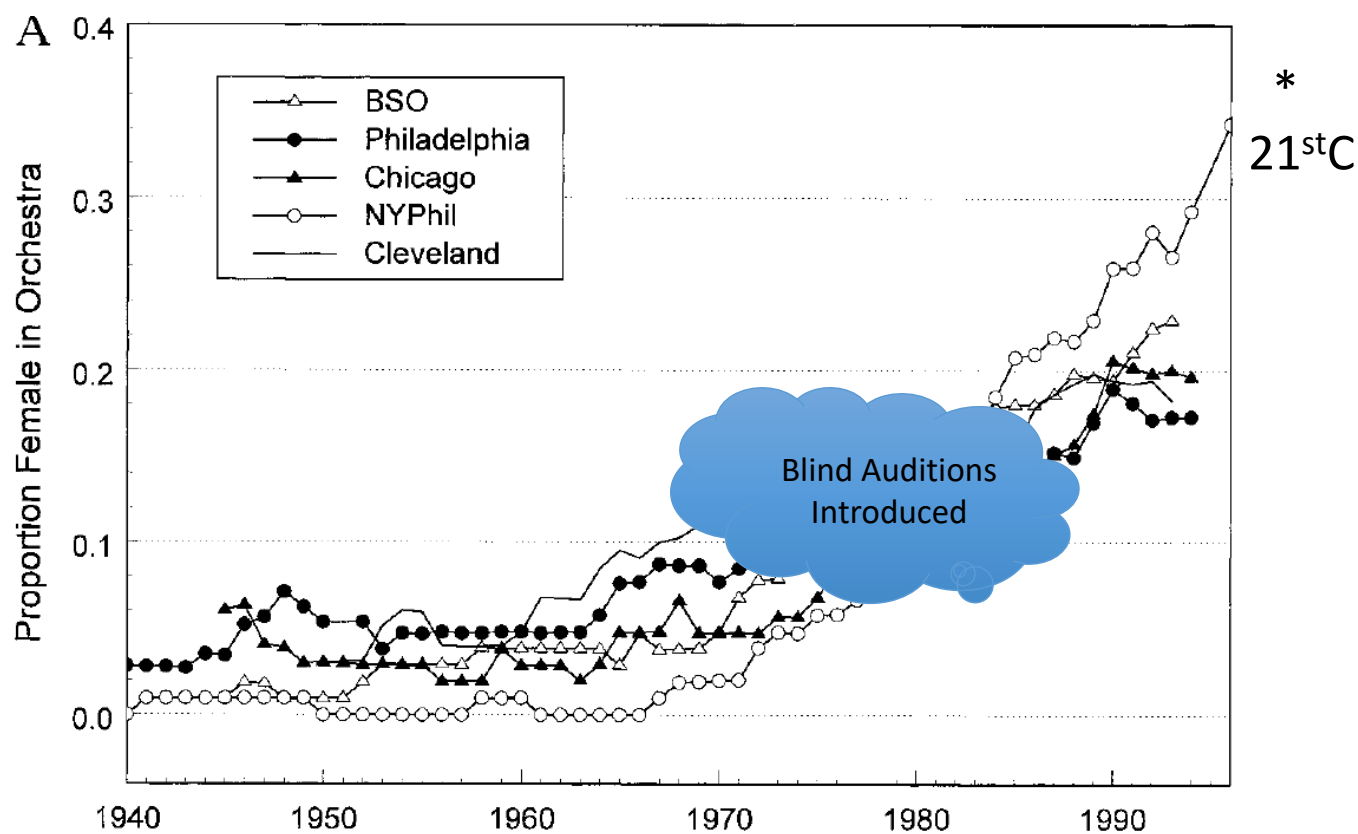
- Definition of a 'good study design'
- Blinding
- Randomization
- The power and peril of pre-specification of endpoints

WHY BLIND?



www.curt-rice.com

Pervasive Attitude Prior to 1970: There is no place for women in orchestra



Goldin & Rouse (2000) *American Economic Review* 90: 715

Blinding

Overestimation of treatment effect size
Increased false positive rate

- Far less uptake than other design principals
 - Resource, culture, practical constraints as primary reasons
 - False belief that it doesn't improve studies
- Reported in only 12% of in vivo papers
- Of these, few provide details on methods of blinding, including which parts of experiment are blinded

META-RESEARCH ARTICLE

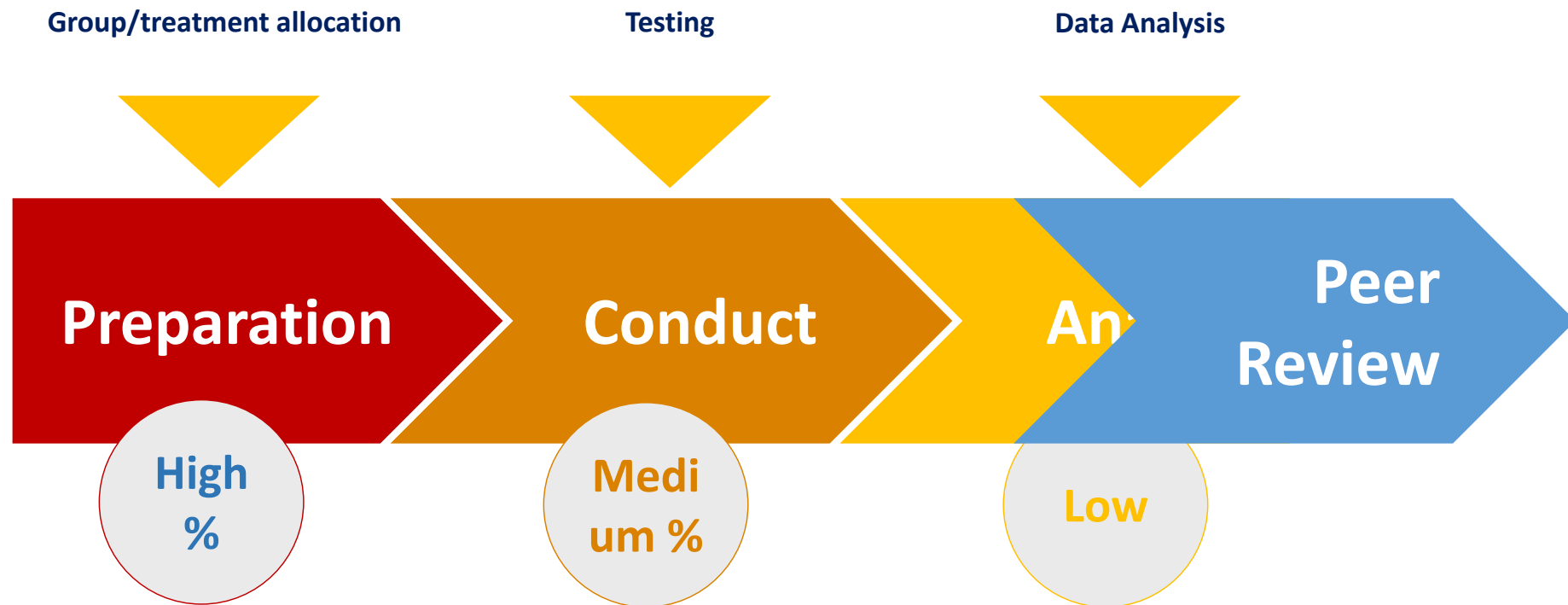
A qualitative study of the barriers to using blinding in in vivo experiments and suggestions for improvement

Natasha A. Karp^{1*}, Esther J. Pearl², Emma J. Stringer³, Chris Barkus², Jane Coates Ulrichsen⁴, Nathalie Percie du Sert²

¹ Data Sciences & Quantitative Biology, Discovery Sciences, R&D, AstraZeneca, Cambridge, United Kingdom, ² NC3Rs, London, United Kingdom, ³ Biomedical Services Unit, University of Birmingham, Birmingham, United Kingdom, ⁴ Early Oncology, AstraZeneca, Cambridge, United Kingdom

• <https://doi.org/10.1371/journal.pbio.3001873>

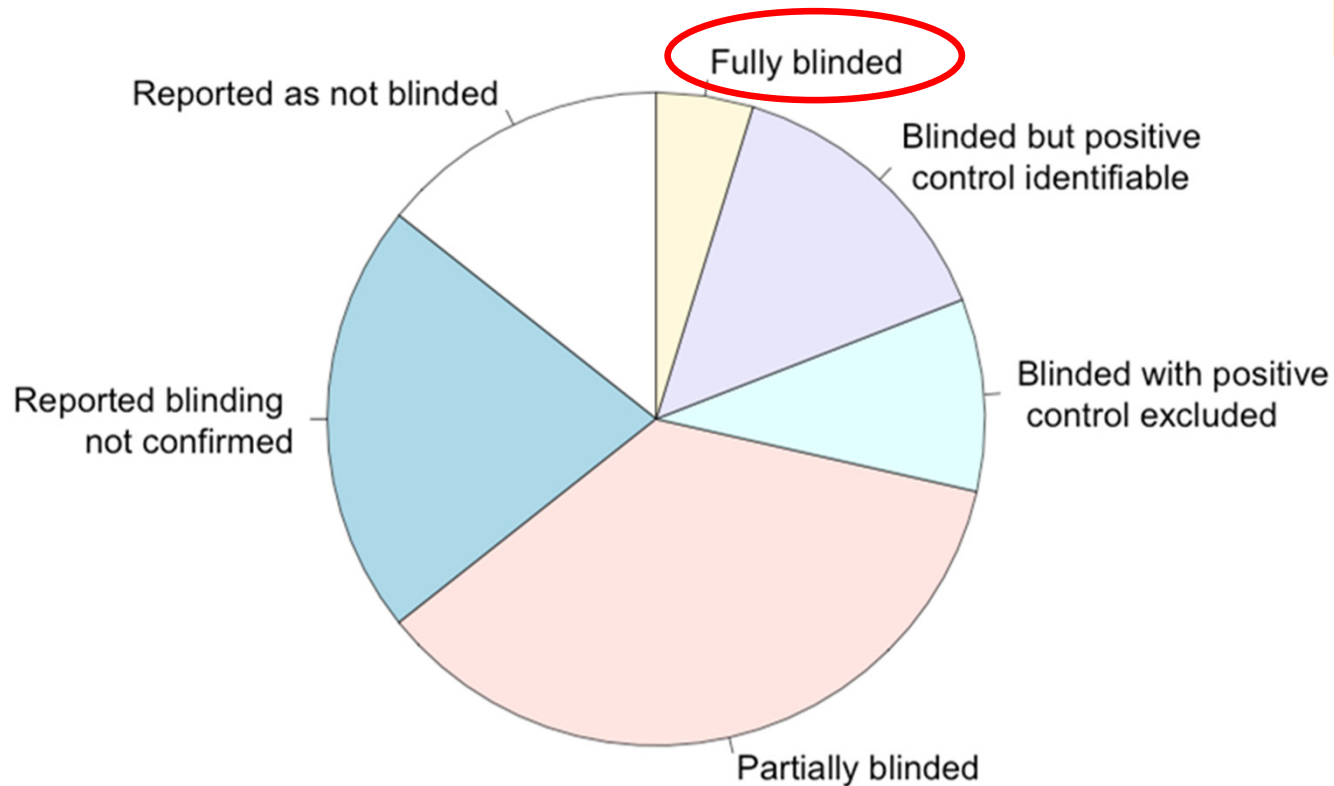
Blinding application by experimental stage



One should expect uniform application, but in principle, not so much

PAASP Survey on Blinding

84 experiments
12 academic labs
7 CROs
4 industry labs



Outline

- Definition of a 'good study'
- Blinding
- Randomization
- The power and peril of pre-specification of endpoints

PAASP Survey on use of randomization

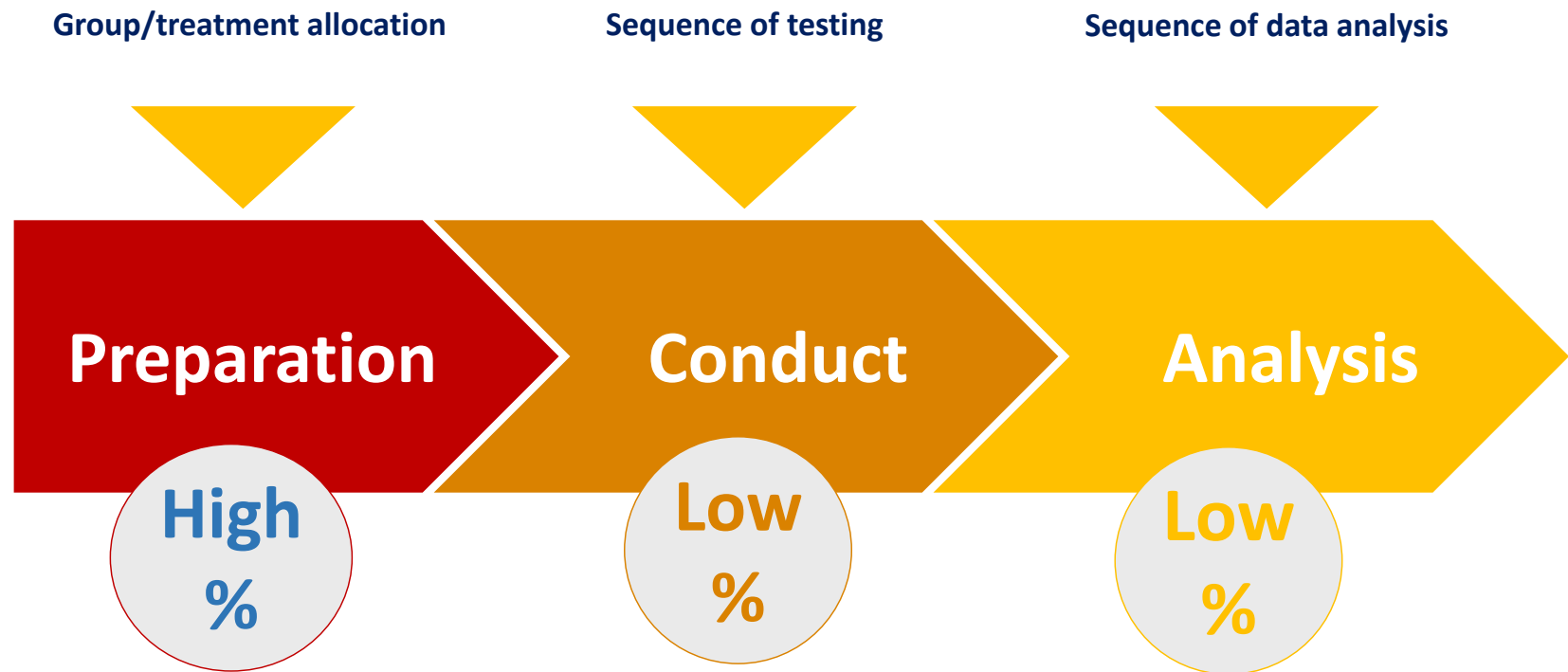
- 30 CROs performing **GLP safety studies** contacted
 - 73% responded (22/30)
 - 45% (10/22) reported applying methods of randomization in all studies
 - 42% (5/12) will apply randomization only when requested by sponsors
 - 45% (10/22) will use a specialized tool to generate randomization sequence (although many, many freely available)



Procedures used for assignment of subjects to treatment groups (multiple answers)

Method	Used	Remark
Simple alternation	64% (9/14)	Not randomization
Matching	71% (10/14)	Not randomization
Latin square	29% (4/14)	Pseudo-randomization
Block design or	36% (5/14)	Ca-ching!
Simple randomization	7% (1/14)	Risk of unbalanced allocation w/ low N

Randomization application by experimental stage



<20%!

What if randomization is not done properly?

- **You** have to decide whether:
 - Can blinding still be applied?
 - Can the impact of stratification variables still be evaluated?
 - Is statistical power reduced and sample sizes need to be increased?
 - Is the statistical method chosen can still be applied?
- **You** have to be transparent about it

Pre-Specification of Endpoints

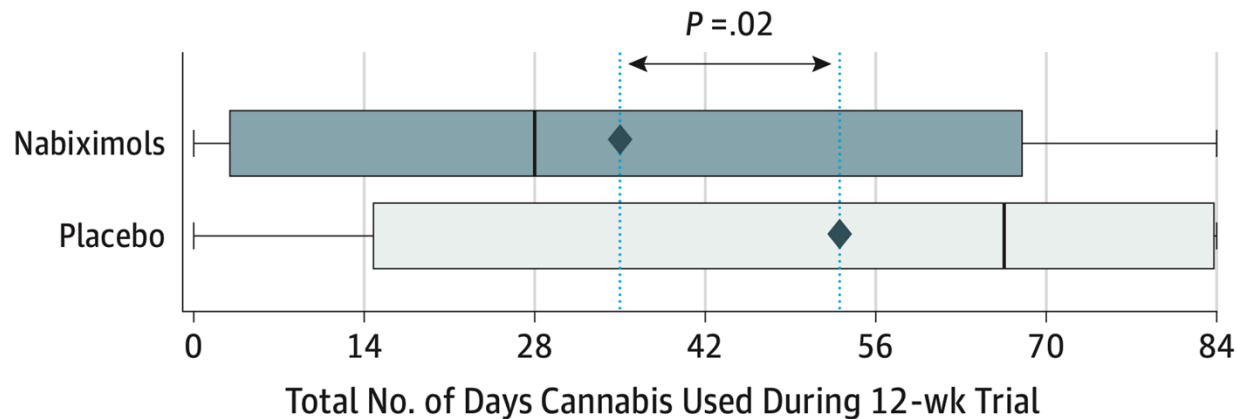
Nabiximols for the Treatment of Cannabis Dependence

A Randomized Clinical Trial

CONCLUSIONS AND RELEVANCE This study demonstrates that cannabinoid agonist treatment, in this case using nabiximols, in combination with psychosocial interventions is a safe approach for reducing cannabis use among individuals with cannabis dependence who are seeking treatment.

JAMA Intern Med. 2019;179(9):1242-1253

- **Primary End Point reported in the paper:**
Frequency of cannabis use
(Self-reported number of days using illicit cannabis during the 12-week period)



Nabiximols for the Treatment of Cannabis Dependence

A Randomized Clinical Trial

CONCLUSIONS AND RELEVANCE This study demonstrates that cannabinoid agonist treatment, in this case using nabiximols, in combination with psychosocial interventions is a safe approach for reducing cannabis use among individuals with cannabis dependence who are seeking treatment.

JAMA Intern Med. 2019;179(9):1242-1253

- **Primary End Point reported in the paper:**

Frequency of cannabis use

(Self-reported number of days using illicit cannabis during the 12-week period)

Reported

Nabiximols for the Treatment of Cannabis Dependence

A Randomized Clinical Trial

CONCLUSIONS AND RELEVANCE This study demonstrates that cannabinoid agonist treatment, in this case using nabiximols, in combination with psychosocial interventions is a safe approach for reducing cannabis use among individuals with cannabis dependence who are seeking treatment.

JAMA Intern Med. 2019;179(9):1242-1253

- **Primary End Point reported in the paper:**

Frequency of cannabis use
(Self-reported number of days using illicit cannabis during the 12-week period)

Reported

- **Primary Outcomes specified in the trial registry and protocol**

A: Unsanctioned cannabis use will be quantified as 4-weekly point prevalence abstinence during the 12-week maintenance phase ... *Unsanctioned cannabis use will also be reported as mean days used*, and percentage of positive urine drug screens.

B: Treatment retention (days in protocol treatment)

Not reported
Reported
Not reported
Reported
(no treatment effect)

Summary

- We can do a much better job of minimizing bias in our studies
- **Blinding** and **randomizing** across all study stages is an initial hassle, but vital in generating repeatable study outcomes
 - GSK and AZ have mandated and enforced rigor for all internal and external in-vivo studies, which has facilitated application in all study types
 - 2024 publication on the ‘what and how’

Free-to-use resources for testing rigor



Experimental
Design
Assistant



National Centre
for the Replacement
Refinement & Reduction
of Animals in Research

[HOME](#) [ABOUT](#) [EXPERIMENTAL DESIGN](#) [USER GUIDE](#) [START PAGE](#)

SEARCH



equator
network

Enhancing the **QUALITY** and
Transparency Of health **Research**



National Institutes
of Health

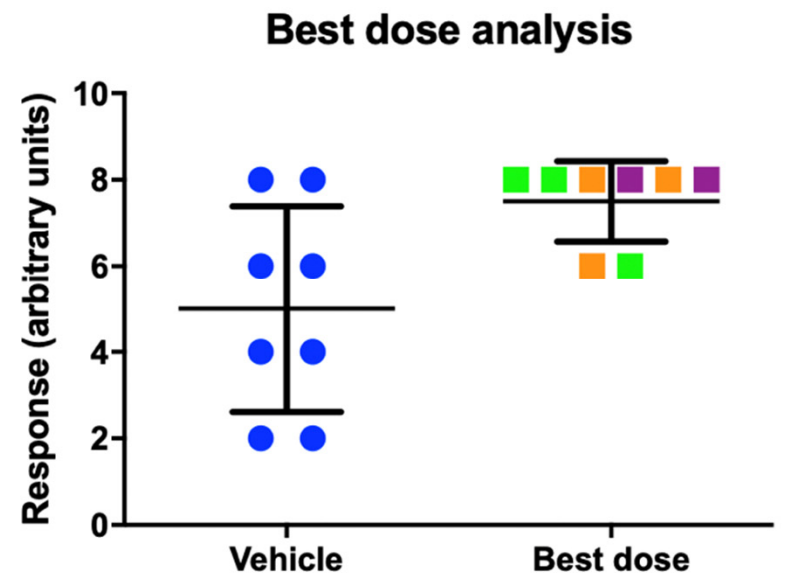
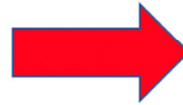
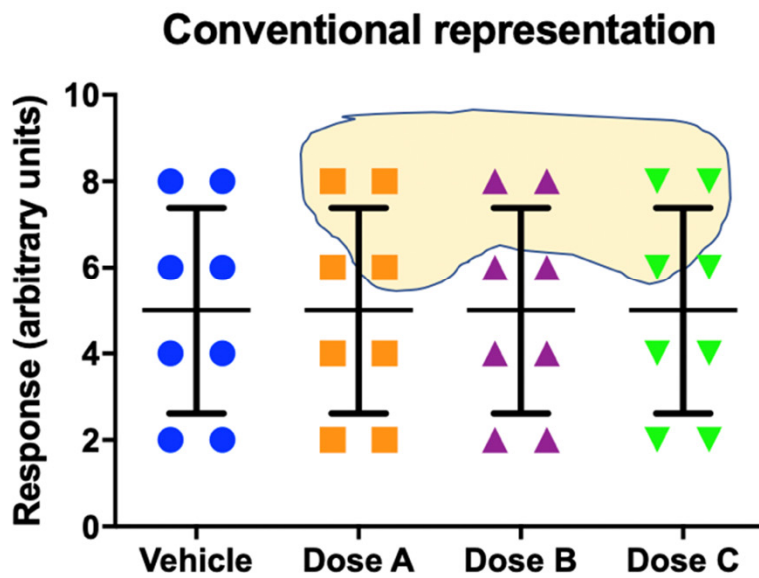
Extras

Heads I win, tails you lose

Scenario	Positive control worked	Positive control failed
My drug worked		???
My drug failed		

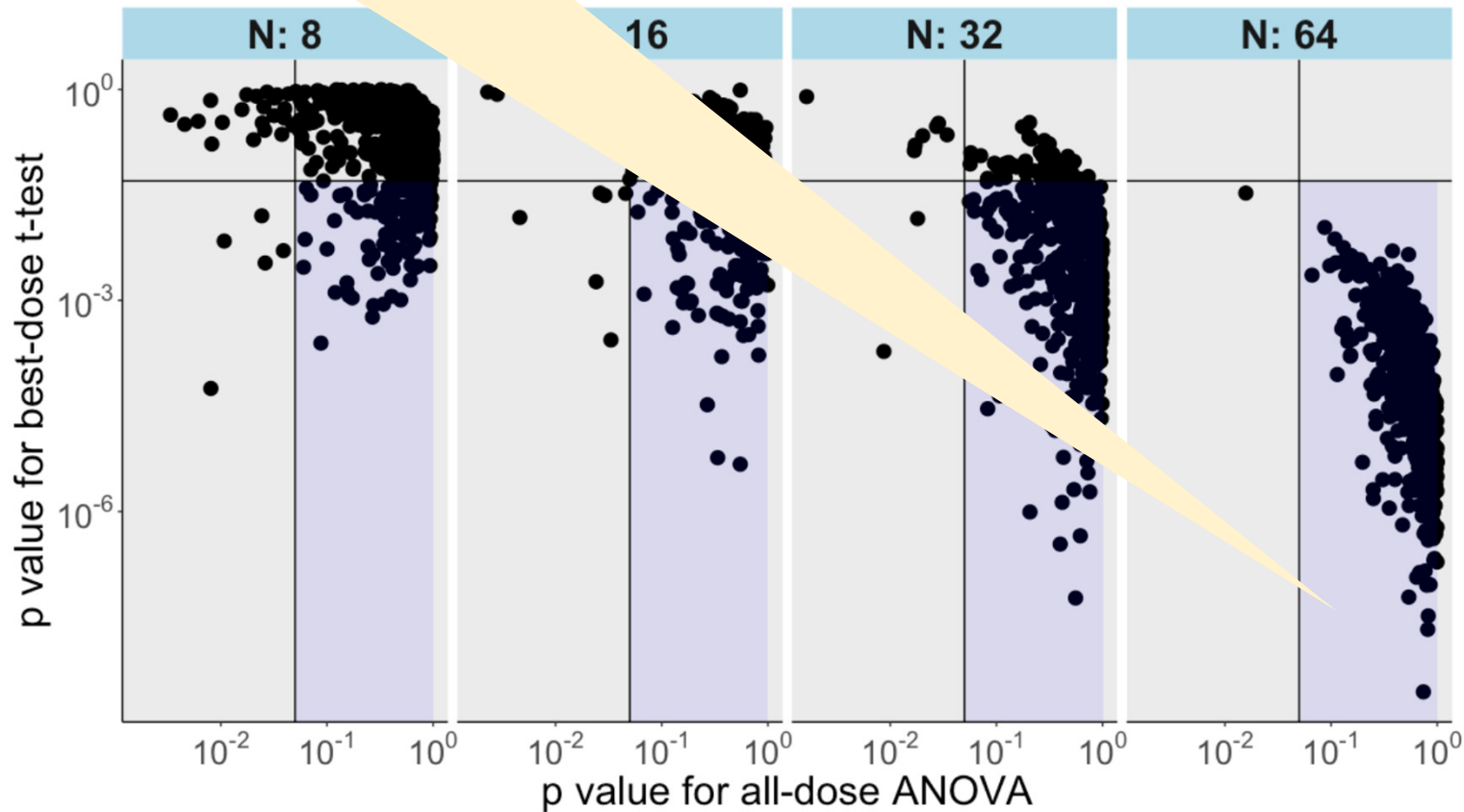
If the use of study outcomes for decision-making is not pre-specified, studies can be designed to bias the interpretation in a favored direction

Heads I win, tails you lose



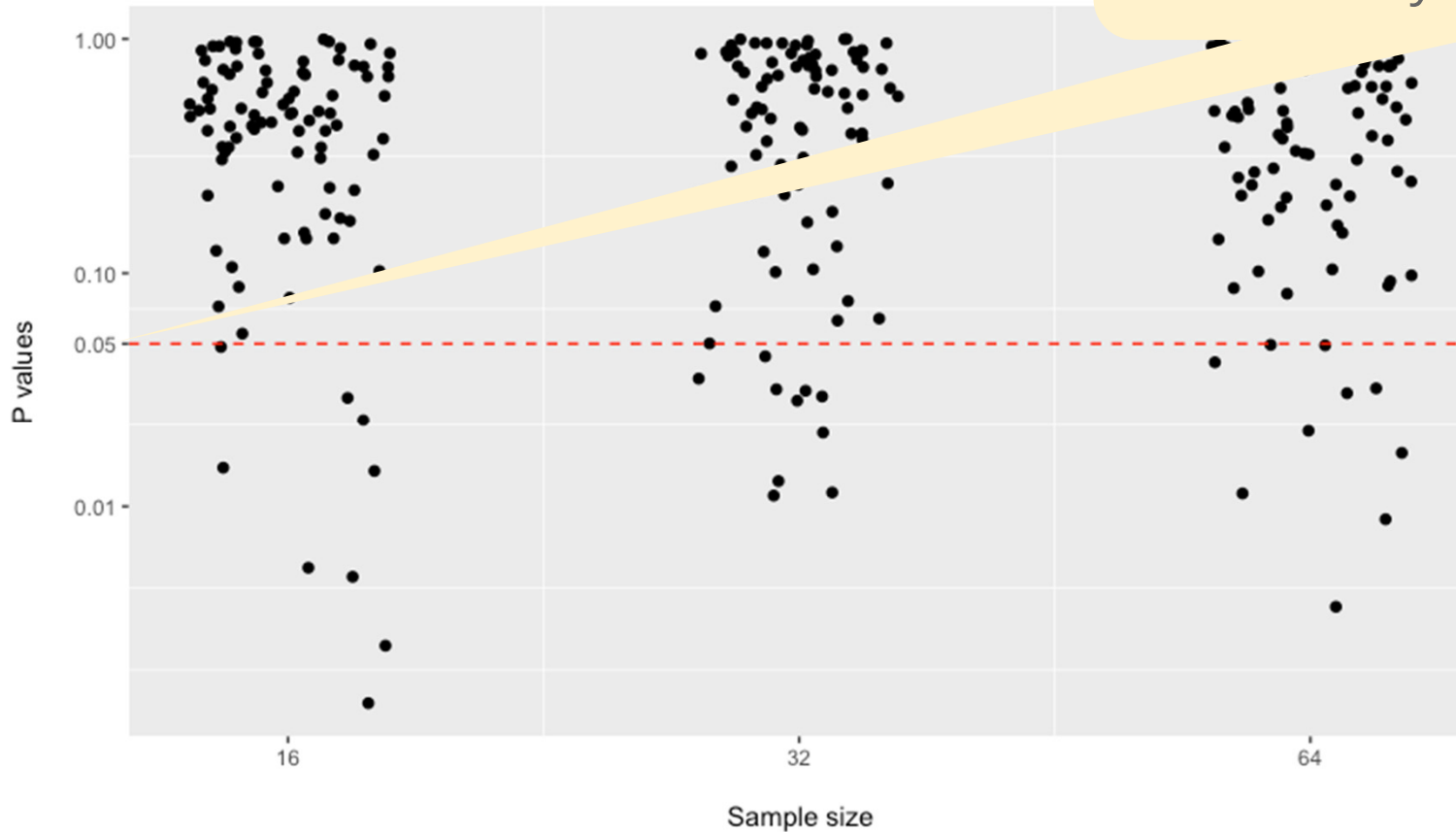
With the sample size large enough, best-dose analysis can turn almost any negative study into positive

you lose



Heads I win, tails you lose

Adding a non-prespecified analysis of sex factor can turn a negative study into „positive“



Two samples drawn from the same normally distributed population and compared by t-test (100 iterations)

Be alerted to false discovery rate!

- Effect size tends to be over-estimated in:
 - under-powered studies
 - studies with low internal validity (i.e. studies with uncontrolled bias)
 - studies reporting „unexpected“ results

Why Most Published Research Findings Are False

John P.A. Ioannidis

PLoS Medicine August 2005 | Volume 2 | Issue 8 | e124

Pre-specification ...

... does not change the data

... builds confidence in data, improves validity

Types of Research Bias:

- 1. Selection Bias**
- 2. Measurement Bias**
- 3. Recall Bias**
- 4. Publication Bias**
- 5. Confirmation Bias**
- 6. Reporting Bias**
- 7. Experimenter Bias**
- 8. Sampling Bias**
- 9. Analysis Selection Bias**
- 10. Procedural Bias**