# Testing for and Evaluating the Extent of Selective Reporting

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- How can we test for (the absence of) selective reporting?
  - > Exploit the distribution of published results t-stats or p-vals
- Challenges:
  - Composite Null p-curve shape depends on power in underlying studies
  - Composite Alternative many ways to p-hack
- This paper derives tests that
  - > Control Type I error over the entire (or mildly restricted) null set
  - More powerful vs. wider range of alternatives relative to existing tests

### One study (absent selection)

Consider study s:  $X_{s,1}, ..., X_{s,n_s} \sim \text{i.i.d. } \mathcal{N}(\mu_s, \sigma_s^2)$ ,  $\sigma_s$  is known

Researchers are testing

 $H_0: E[X_s] = 0$  against  $H_1: E[X_s] \neq 0$ .

• *t*-statistic

$$T_{s} = \frac{\sqrt{n_{s}}\bar{X}_{s}}{\sigma_{s}} = \frac{\sqrt{n_{s}}\mu_{s}}{\sigma_{s}} + \frac{\sqrt{n_{s}}(\bar{X}_{s} - \mu_{s})}{\sigma_{s}} = \underbrace{h_{s}}_{\text{(local) alternative/effect}} + \underbrace{W_{s}}_{\sim \mathcal{N}(0,1)}$$

• What is the power at significance level p?

$$\beta(p, h_s) = \Pr(|T_s| > \operatorname{cv}(p) \mid h_s) = \Pr(p_s \le p \mid h_s)$$
  
= 2 - \Phi(\mathbf{cv}(p) - h\_s) - \Phi(\mathbf{cv}(p) + h\_s) \leftarrow known function

• Immediate generalization to testing problems with *limiting normal experiments* (asy. *t*-tests)

## Literature (absent selection)



Treat *h* as random:  $h \sim \Pi \Rightarrow$  Distribution of  $p_s$ :  $G_0(p) = \int \beta(p, h) d\Pi(h)$ 



The *p*-curve shape depends on the *distribution of effects in the literature* 

• or the implied distribution of power



$$\mathcal{G}_0 := \left\{ G_0 \mid G_0(p) = \int_{\mathbb{R}} \beta(p,h) d\Pi(h), \quad \Pi \in \{\text{all probability distributions}\} \right\}$$

No selective reporting:  $H_0: \ G \in \mathcal{G}_0$ 





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No selective reporting:  $H_0: G \in \mathcal{G}_0$ 

**Existing Tests:** testable implications  $\mathcal{G}_0 \subset \mathcal{G}_*$ :

- Continuity
- (Complete) Monotonicity
- Bounds





#### New (More Powerful) Tests



Non-parametric step - requires regularization (Kernel Deconvolution)

#### New (More Powerful) Tests



Convenient to bypass estimation of  $\Pi$  and focus on  $G_0(\Pi)$ 

#### New (More Powerful) Tests



- Kolmogorov-Smirnov (KS) distance:  $T_{\infty} := \left| \left| \widehat{G} \widetilde{G} \right| \right|_{\infty}$
- Distance between histograms:  $\widehat{G}(x_1) \widetilde{G}(x_1), \dots, \widehat{G}(x_J) \widetilde{G}(x_J)$

## Alternative: Which Distributions indicate Selective Reporting?





Both! Each contains  $100 \times \tau$ % of results reported selectively. (Here  $\tau = 0.5$ )





- Thresholding and Minimum approaches
- *p*-hacking "slow" and "fast" (Data Colada terminology)
- Generate very different distributions

#### **Power Improvements**

- DGPs tailored to existing dataset of published results
- Two types of *p*-hacking as before
- Sample size 1000



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Additionally, provide a lower bound estimate on  $\tau$