

A Bayesian Meta-analysis Method that Corrects for Publication Bias

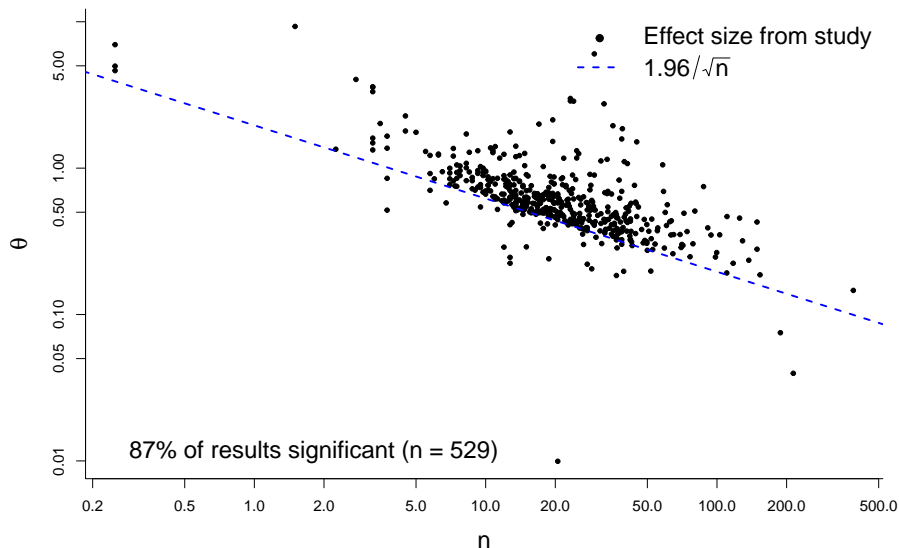
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June 26, 2018

Nordstat 2018

This is What p -hacking Looks Like!



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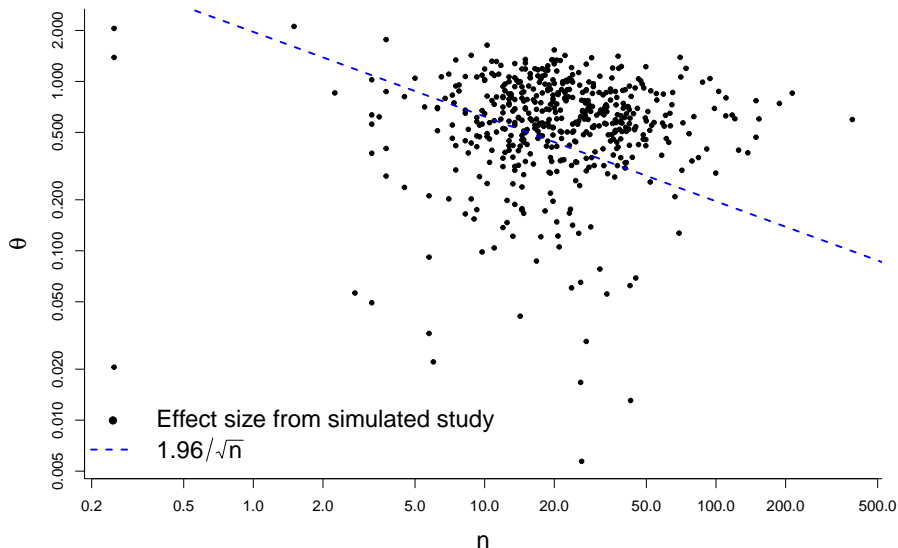
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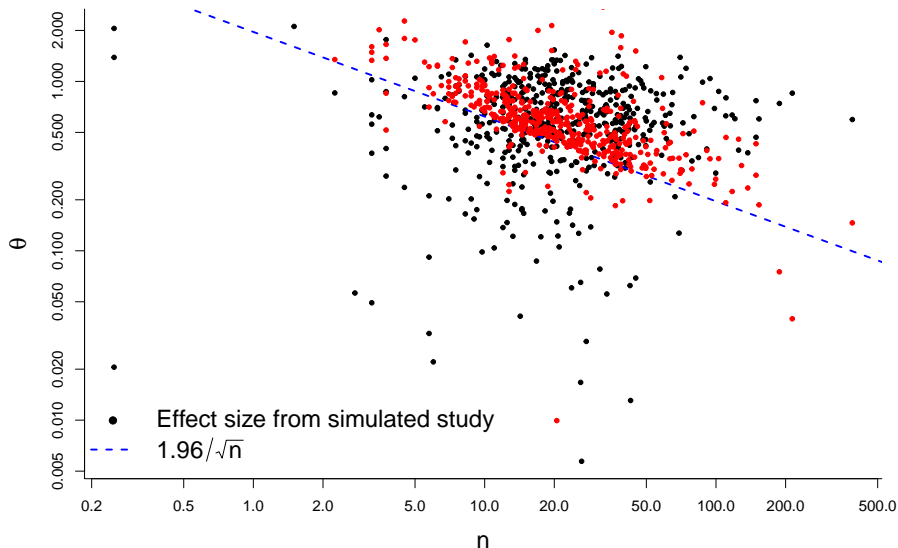
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- **Question:** Is the classical model realistic in presence of p -hacking?

What the Previous Plot *Should Have* Looked Like!



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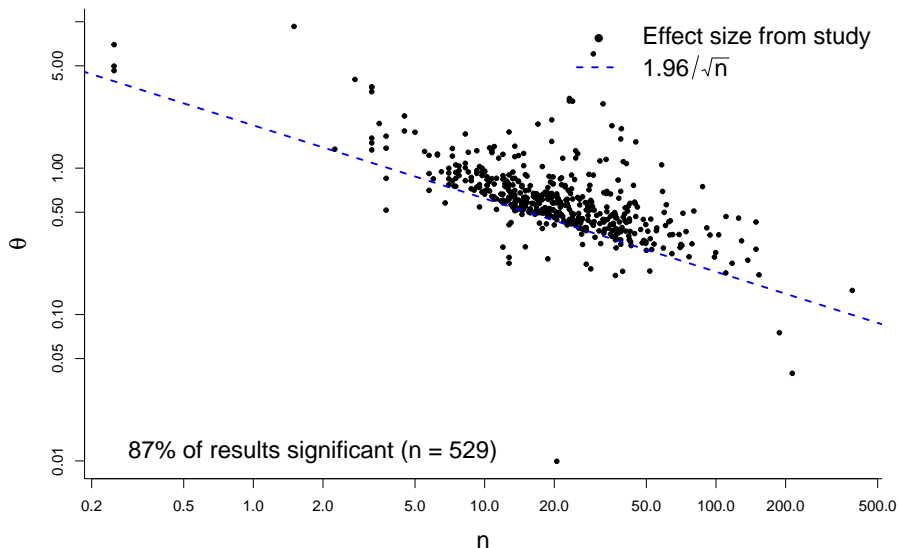
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- **Problem:** The first plot also contains studies that weren't affected by selection for significance!

Revisiting the First Plot



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- On to examples!

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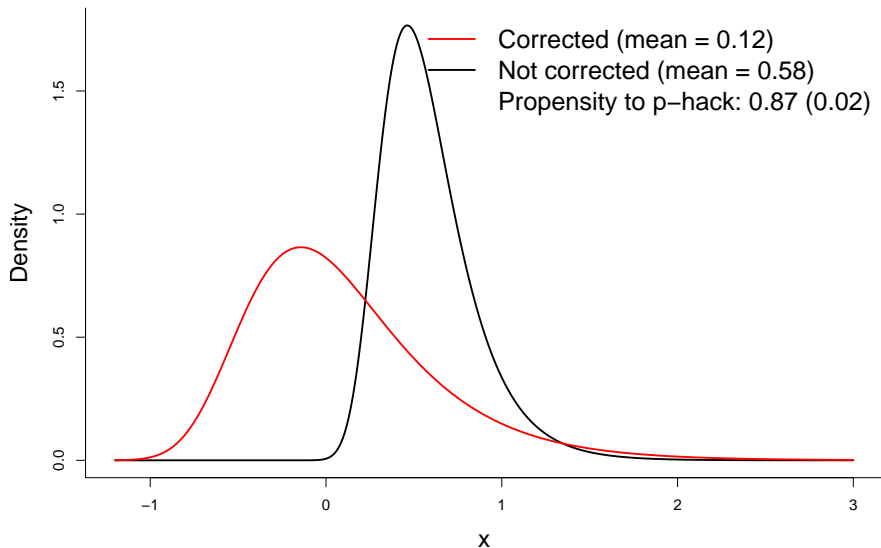
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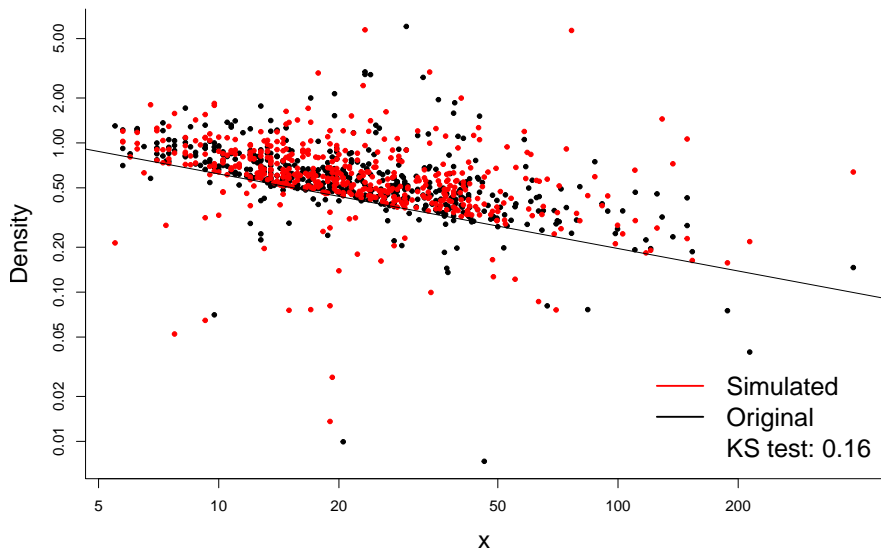
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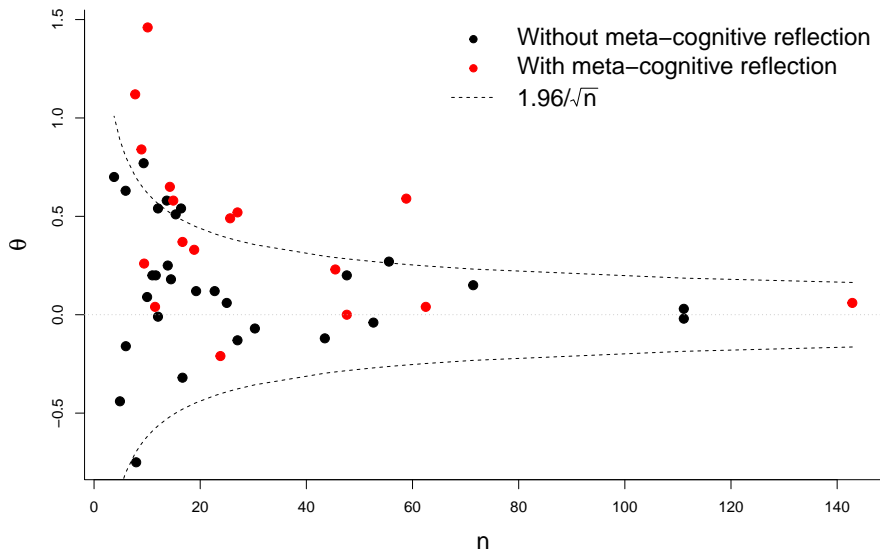
Posterior Predictive Distributions



A Simulation from the Posterior



Bangert-Drowns, Hurley & Wilkinson (2004)



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 - ▶ Does p -hacking change the estimated effect sizes?

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Model	θ_0	θ_M	σ	p
Corrected	0.02(0.06)	0.14(0.16)	0.1(0.1)	0.3(0.07)
Not corrected	0.14(0.05)	0.21(0.10)	0.2(0.05)	NA

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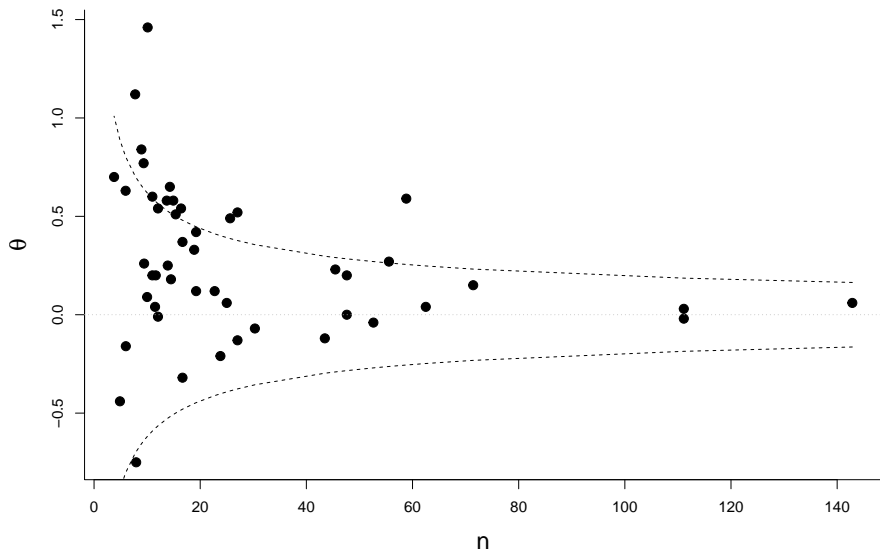
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- Publication is easier with larger n .

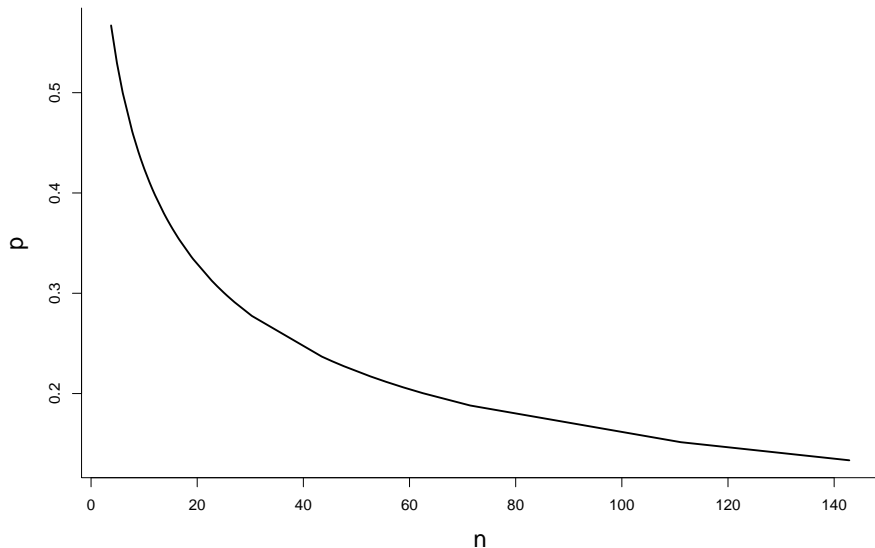
Visually Evidence for Logistic Regression on p



Results without Meta-cognition

Model	θ_0	σ	p_0	p_1
Random effects	0.07(0.07)	0.1(0.05)	-0.7(0.3)	-0.5(0.3)
Fixed effects	0.04(0.07)	NA	-0.8(0.3)	-0.6(0.4)

The Shape of the p -hacking Propensity



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- An R-package at GitHub:

`straussR`

Statistical Reanalysis under Selection for Significance

<https://github.com/JonasMoss/straussR>