

Suspect Research & Statistical Inferences

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Suspect research practices

- Suspect practices *can* lead to inaccurate findings (e.g., Hedges, 2017; Lindsay, 2012).
- How much? Depends on which suspect practice. . .
- Conditional data collection: failing significance, get more data!?
 1. Bias treatment effect estimates
 2. Bias can be large (~50%)
 3. Bias can arise even if no analyses are conducted

Conditional data collection

- John, Loewenstein, & Prelec (2012): $>50\%$ of respondents admitted they had collected more data based on a nonsignificant result.
- Fiedler & Schwartz (2016): $>30\%$ of respondents admitted to collecting more data in order to render a nonsignificant result significant.
- Simmons, Nelson, & Simonsohn (2011): Inflated type I error rates ($\sim 10\text{-}20\%$)
- Related to sequential trials in medicine (Nardini & Sprenger, 2012)

Conditional data collection

- Treatment effect $\theta \neq 0$
- Initial experiment (n subjects in each of treatment & control)
 - Estimate T_0 (mean difference)
- Concomitant variable O correlated with T_0
- Based on O either:
 1. Report T_0
 2. Continue experiment
 - ▶ Recruit more subjects (m subjects per arm)
 - ▶ Report T_1

Conditional inferences

- We only observe an estimate conditional on O :
 1. $T_0|O$
 2. $T_1|O$
- Bias:
 1. $E[T_0|O] - \theta$
 2. $E[T_1|O] = \frac{n}{m+n} (E[T_0|O] - \theta)$
- **If O is correlated to T_0 , the treatment effect can be biased.**

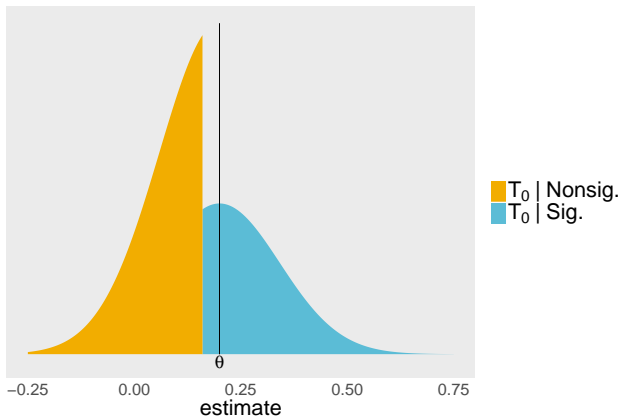
Model

1. Data are normally distributed, with known variance.
2. n subjects per arm in initial experiment
 - $T_0 \sim N(\theta, 2\sigma^2/n)$
3. m subjects added per arm, whose responses are independent of past observations.

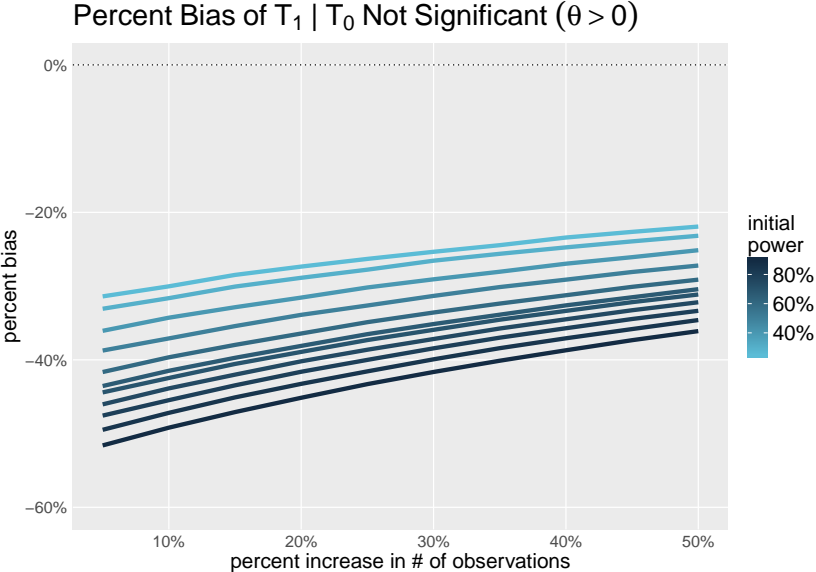
Conditional on significance

- $O = \mathbf{1}\{|T_0| > 1.96\sqrt{2\sigma^2/n}\}$; ($\alpha = .05$, 2-tailed test)
- Stop if $O = 1$, continue if $O = 0$
- T_0 will be a truncated normal

Distribution of $T_0 | O$



Collecting data based on nonsignificance



Other concomitant variables

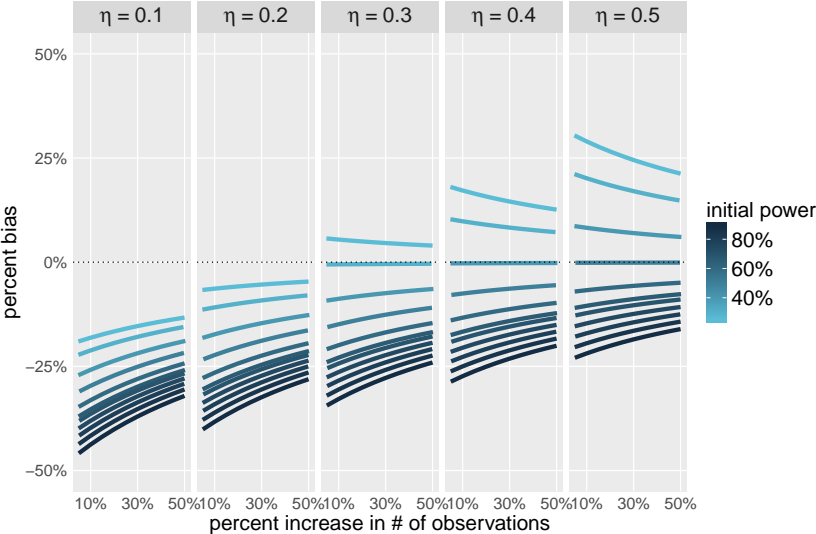
- “If O is correlated to T_0 , the treatment effect can be biased.”
 - Me, three slides ago.
- Researchers may observe any number of variables correlated with T_0 .
 - Casual observations may be correlated with T_0 .
 - If more data are collected based on them, $T_1|O$ can be biased.
 - No analysis of initial data needed.
- How might these variables convey information about T_0 ?
 - How likely is it that T_0 will be significant given what was observed?

Information about possible significance

- Probabilistic model
- O provides information about how likely T_0 is to be significant:
 - $P[T_0 \text{ significant} | O] = \eta$
- For a given probability of significance (η), a researcher may
 - stop and report $T_0 | \eta$
 - collect more data and report $T_1 | \eta$
- Assume O conveys *only* information about the probability of significance.
 - $T_0 | O$ has a reweighted normal distribution

Continuing due to improbable significance

Percent Bias of T_1 | $P [T_0 \text{ Significant} | O] = \eta$



Unknowable bias

- It may be impossible to determine exactly what information any observation conveys about T_0 .
- If it carries *any* information, and the decision to collect more data depends on it, we know that T_1 can be biased.
- We may have no idea how biased a given result is.
- **Ad-hoc data collection can bias a treatment effect estimate even if no analysis of interim data is conducted. It may be impossible to know how much this bias is!**

Conclusions

- Bias from conditionally collected data can be substantial, even if a researcher does not actually run a significance test.
- Pre-registration can improve transparency, and help curtail more passive forms of CDC.
 - SREE!
- Blinding?
- Empirical replication of past results.

References

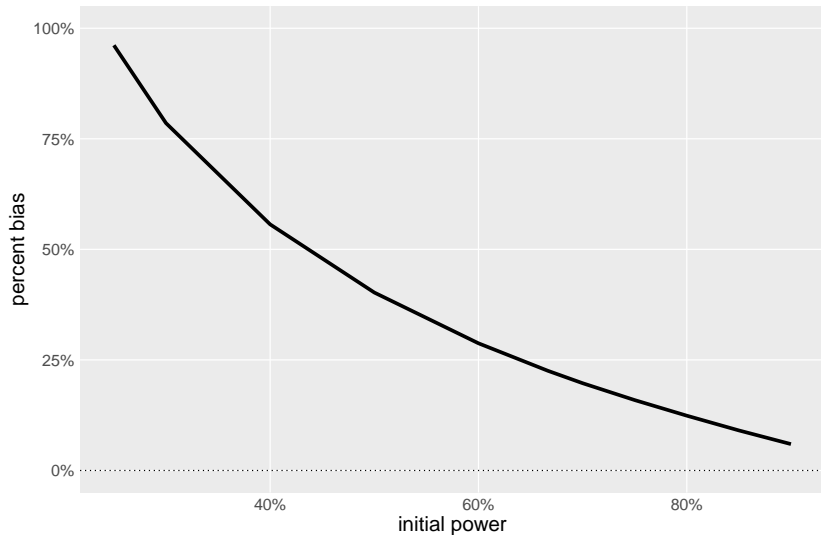
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Thank You!

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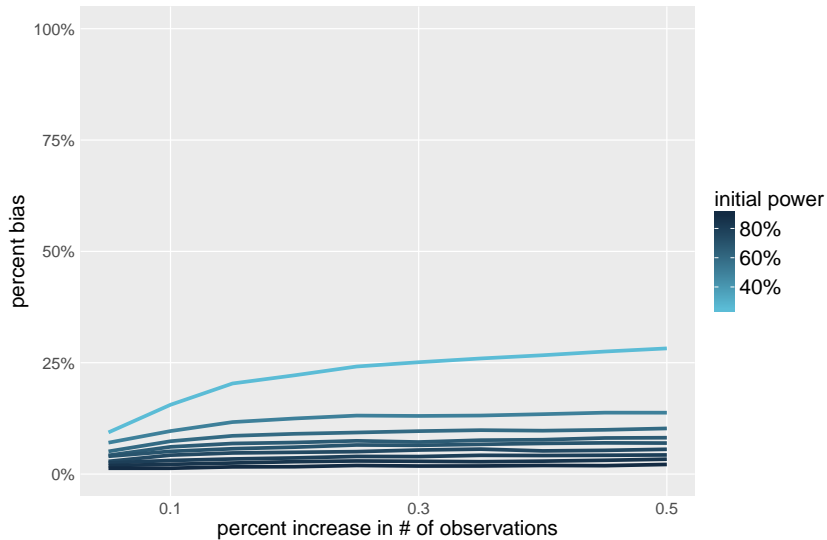
Stopping for significance

Percent Bias of T_0 | T_0 Significant



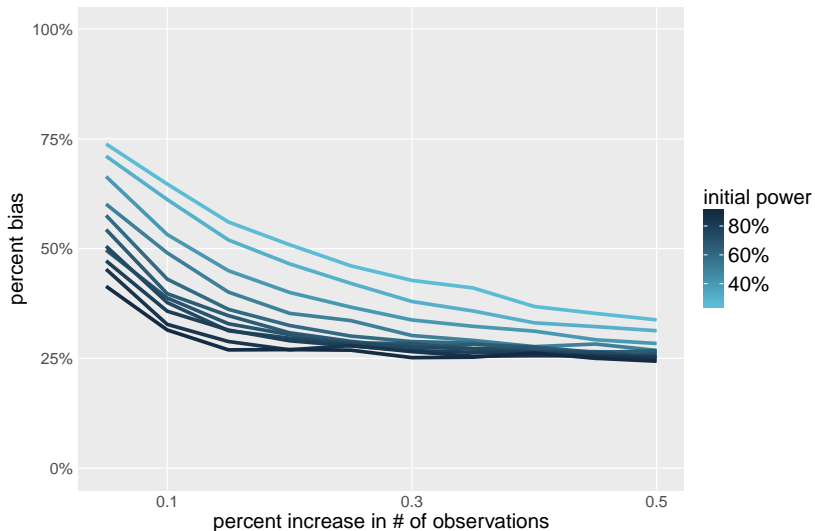
Repeated waves

Percent Bias of $T_k | T_{k-1}$ Not Significant

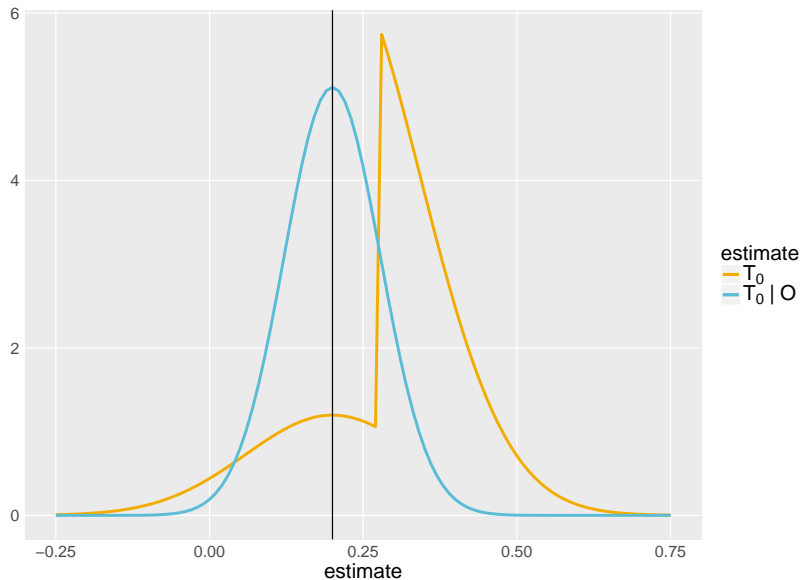


Repeated waves, reporting only significant results

Percent Bias of T_k | T_{k-1} Not Significant : Only Significant Fil



Distributions: probable significance



Stopping for probable significance

Percent Bias of T_0 | $P [T_0 \text{ Significant} | O] = \eta$

