

Which findings get published?  
Which findings should be published?

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# Introduction

- Replicability is a fundamental requirement of science. Different researchers should reach the same conclusions. Methodological conventions should ensure this.
- Replications of published experiments frequently find effects which are of smaller magnitude or opposite sign.
- One explanation: Selective publication based on findings.

## 1. Publication bias

- Journal editor and referee decisions.
- Statistical significance, surprisingness, or confirmation of prior beliefs.

## 2. P-hacking and specification searching

- Researcher decisions.
- Incentives to select which findings to submit based on the likelihood of publication.

# Two questions

## 1. Which findings get published?

- How much and based on what criteria are findings selected?
- How can we correct for such selection?
- Existing approaches test whether publication is selective, but do not estimate the amount and form of selection.

## 2. Which findings should be published?

- Replicability is not the only goal of research.
- Relevance for policy (and other) decisions is important, as well.
- These two goals might potentially stand in conflict.
- Existing reform proposals focus on replicability and aim to eliminate selection, ignoring the role of relevance.

*Andrews, I. and Kasy, M. (2018). Identification of and correction for publication bias*

*Frankel, A. and Kasy, M. (2018). Which findings should be published?*

# Roadmap

## I Which findings get published?

- 1 Setup and bias-corrected inference
- 2 Identification
  - a Replication studies
  - b Meta-studies
- 3 Application: Lab experiments in economics

## II Which findings should be published?

- 1 Setup and optimal publication rules
- 2 Selective publication and statistical inference.
- 3 Extensions
  - a Dynamic model
  - b Researcher incentives

Conclusion

# Part I: Which findings get published?

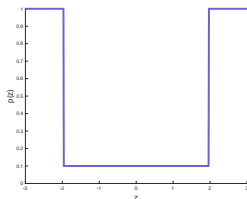
## Key results

1. If form and magnitude of selection are known, we **can correct published findings**.
  - Unbiased estimates, confidence sets that control size.
  - Using “quantile inversion.”
2. Form and magnitude of **selection** are **nonparametrically identified**.
  - Using systematic replication studies.
  - Using meta-studies.
3. **Published research is selected:**
  - Lab experiments in economics and psychology:  
Statistical significance
  - Effect of minimum wages on employment:  
Statistical significance, sign.
  - Deworming:  
Inconclusive.

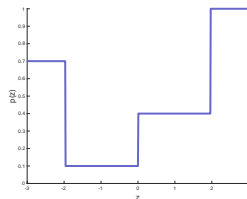
# Setup

Examples: Possible forms of selection  $p(Z)$

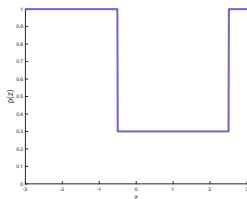
Significance



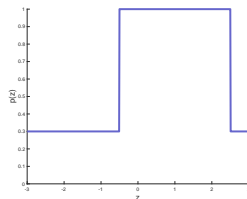
Significance and sign



Surprisingness



Plausibility



- $p(Z)$ : Probability that an estimate  $Z$  is published.

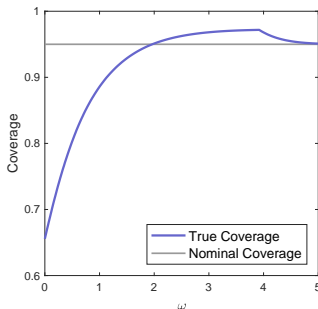
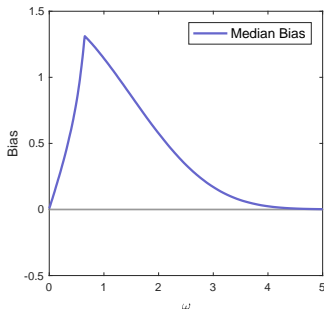
# Setup

## Assumptions and notation

<b>Latent studies</b>	
True parameter value	$\Theta^*$
Standard error	$\sigma^*$
Distribution across studies	$(\Theta^*, \sigma^*) \sim \pi_{\Theta, \sigma}$
<b>Reported estimate</b>	
Distribution	$X^*   \Theta^*, \sigma^* \sim N(\Theta^*, \sigma^{*2})$
z-statistic, normalized parameter	$Z^* = \frac{X^*}{\sigma^*}, \Omega^* = \frac{\Theta^*}{\sigma^*}$
<b>Publication decision</b>	
Publication probability	$p(Z)$
Publication event	$D   X^*, \Theta^*, \sigma^* \sim \text{Ber}(p(Z^*))$
<b>Observed sample</b>	
Observed variables	i.i.d. given $D = 1$ $(X, \sigma)$

# Publication bias

Example: Selection on significance



- Publication probability: “significance testing,”

$$p(z) = \begin{cases} 0.1 & |z| < 1.96 \\ 1 & |z| \geq 1.96 \end{cases}$$

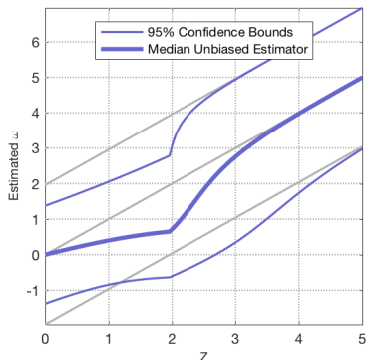
left median bias of  $\hat{\omega} = Z$

right true coverage of conventional 95% confidence interval



# Bias-corrected inference

Example: selection on significance



- If we know  $p(\cdot)$ , can we correct for bias and size distortions?
- Publication probability: “significance testing,”

$$p(z) = \begin{cases} 0.1 & |z| < 1.96 \\ 1 & |z| \geq 1.96 \end{cases}$$

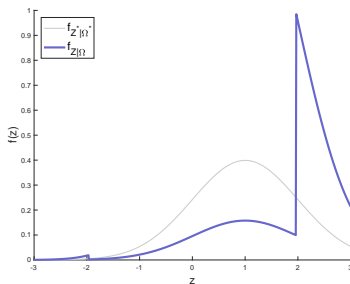
# Bias-corrected inference

## Density of published estimates

- How was this figure constructed?
- Density of published  $Z$  given  $\Omega$ :

$$\begin{aligned}f_{Z|\Omega,\sigma}(z|\omega,\sigma) &= f_{Z^*|\Omega^*,\sigma^*,D}(z|\omega,\sigma,1) \\ &= \frac{p(z)}{E[p(Z^*)|\Omega^* = \omega]} \varphi(z - \omega).\end{aligned}$$

- Example: Selection on significance.



- Corresponding cumulative distribution function:  $F_{Z|\Omega}(z|\omega)$

# Bias-corrected inference

## Corrected frequentist estimators and confidence sets

- Define  $\hat{\omega}_\alpha(z)$  via

$$F_{Z|\Omega}(z|\hat{\omega}_\alpha(z)) = \alpha.$$

- This definition implies that

$$P(\hat{\omega}_\alpha(Z) \leq \omega | \Omega = \omega) = \alpha \quad \forall \omega.$$

- Median-unbiased estimator:  $\hat{\omega}_{\frac{1}{2}}(Z)$  for  $\omega$ .
- Equal-tailed level  $1 - \alpha$  confidence interval:

$$\left[ \hat{\omega}_{\frac{\alpha}{2}}(Z), \hat{\omega}_{1-\frac{\alpha}{2}}(Z) \right]$$

# Roadmap

## I Which findings get published?

1 Setup and bias-corrected inference

2 **Identification**

a Replication studies

b Meta-studies

3 Application: Lab experiments in economics

## II Which findings should be published?

1 Setup and optimal publication rules

2 Selective publication and statistical inference

3 Extensions

a Dynamic model.

b Researcher incentives

Conclusion

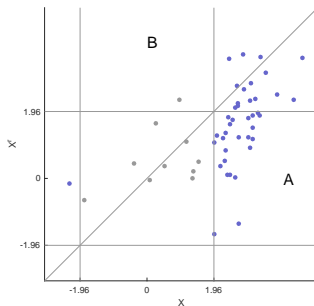
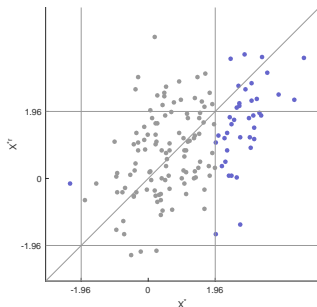
# Identification

## Identification of the selection mechanism $p(\cdot)$

- We propose two approaches for identification of  $p(\cdot)$ :
  1. Systematic replication experiments:
    - Replication estimates for the same parameters.
    - Selectivity operates only on original estimate, but not on replication estimate.
  2. Meta-studies:
    - Leveraging variation in  $\sigma^*$ .
    - Assume  $\sigma^*$  is (conditionally) independent of  $\Theta^*$  across latent studies.
    - Standard assumption in the meta-studies literature; validated in our applications by comparison to replications.
- Advantages:
  1. Replications: Very credible
  2. Meta-studies: Widely applicable

# Identification

Intuition for approach 1: Identification using replication studies



left No truncation

$\Rightarrow$  Areas  $A$  and  $B$  have same probability.

right  $A$  more likely than  $B$ .

$$p(z) = \begin{cases} 0.1 & |z| < 1.96 \\ 1 & |z| \geq 1.96 \end{cases}$$

# Identification

## Approach 1: Replication studies

- Consider the general setup introduced above.
- Assume that for each published estimate we **additionally observe a replication draw**  $X^r$  as well as  $\sigma^{r2}$  such that

$$X^{*r} | \Theta^*, \sigma^{*r}, \sigma^*, D, X^* \sim N(\Theta^*, \sigma^{*r2}).$$

- **Then  $p(\cdot)$  is identified** up to scale, and  $\pi_\Theta$  is identified as well.

Sketch of proof:

- Consider the special case  $\sigma^{*r} = \sigma^*$ .
- Marginal density of  $(X, X^r)$  is

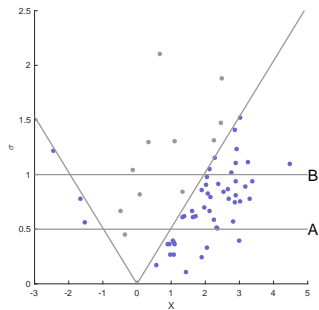
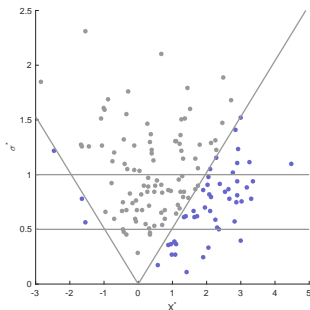
$$f_{Z, Z^r}(z, z^r) = \frac{p(z)}{E[p(Z^*)]} \int \varphi(z - \omega) \varphi(z^r - \omega) d\pi_\Omega(\omega).$$

- Thus, for all  $a, b$ , if  $p(a) > 0$ ,

$$\frac{f_{Z, Z^r}(b, a)}{f_{Z, Z^r}(a, b)} = \frac{p(b)}{p(a)}.$$

# Identification

## Intuition for Approach 2: Identification using meta-studies



left No truncation

$\Rightarrow$  Dist for higher  $\sigma$  noised up version of dist for lower  $\sigma$ .

right "Missing data" inside the cone.

$$p(z) = \begin{cases} 0.1 & |z| < 1.96 \\ 1 & |z| \geq 1.96 \end{cases}$$



# Identification

## Approach 2: Meta-studies

- Consider the general setup introduced above.
- Assume additionally that  $\sigma^*$  and  $\Theta^*$  are independent, and suppose that the support of  $\sigma$  contains an open interval.
- Then  $p(\cdot)$  is identified up to scale, and  $\pi_\Theta$  is identified as well.

Sketch of proof:

- Conditional density of  $Z$  given  $\sigma$  is

$$f_{Z|\sigma}(z|\sigma) = \frac{p(z)}{E[p(Z^*)|\sigma]} \int \varphi(z - \theta/\sigma) d\pi(\theta).$$

- Thus

$$\frac{f_{Z|\sigma}(z|\sigma_2)}{f_{Z|\sigma}(z|\sigma_1)} = \frac{E[p(Z^*)|\sigma = \sigma_1]}{E[p(Z^*)|\sigma = \sigma_2]} \cdot \frac{\int \varphi(z - \theta/\sigma_2) d\pi(\theta)}{\int \varphi(z - \theta/\sigma_1) d\pi(\theta)}.$$

- Recover  $\pi$  from right hand side, then recover  $p(\cdot)$  from first equation.

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3 **Application: Lab experiments in economics**

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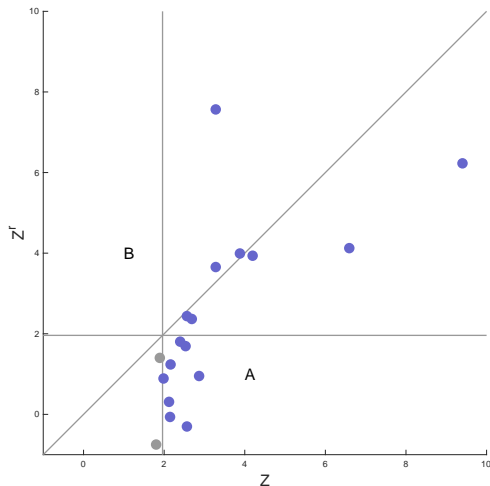
# Application

## Replications of Lab Experiments in Economics

- Camerer et al. (2016)
- Sample: all 18 between-subject laboratory experimental papers published in AER and QJE between 2011 and 2014.
- Scatterplot next slide:
  - $Z = X/\sigma$ : normalized initial estimate.
  - $Z^r = X^r/\sigma$ : replicate estimate.
  - Initial estimates normalized to be positive.

# Application

## Economics Lab Experiments: Original and Replication Z Statistics



# Application

## Economics Lab Experiments: Estimates of Selection model

- Model:

$$|\Omega^*| \sim \Gamma(\kappa, \lambda)$$
$$p(Z) \propto \begin{cases} \beta_p & |Z| < 1.96 \\ 1 & |Z| \geq 1.96 \end{cases}$$

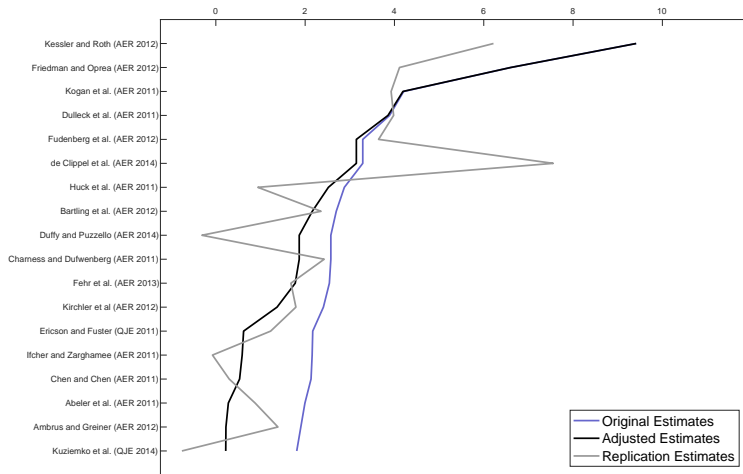
- Estimates:

$\kappa$	$\lambda$	$\beta_p$
0.373	2.153	0.029
(0.266)	(1.024)	(0.027)

- Interpretation: Insignificant (at the 5 % level) results about 3% as likely to be published as significant results.

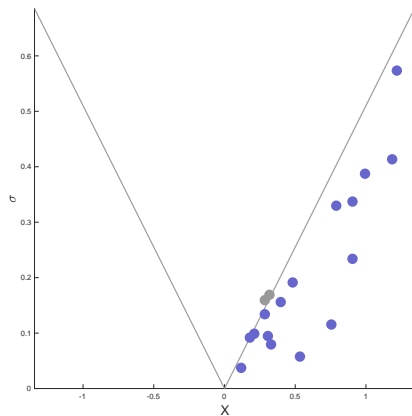
# Application

## Economics Lab Experiments: Adjusted Estimates



# Application

## Economics Lab Experiments: Meta-study Approach



# Application

## Economics Lab Experiments: Meta-study Results

- Model:

$$|\Theta^*| \sim \Gamma(\tilde{\kappa}, \tilde{\lambda})$$

$$p(Z) \propto \begin{cases} \beta_p & |Z| < 1.96 \\ 1 & |Z| \geq 1.96 \end{cases}$$

- Recall replication-based estimates:

$\kappa$	$\lambda$	$\beta_p$
0.373	2.153	0.029
(0.266)	(1.024)	(0.027)

- Meta-study based estimates (only  $\beta_p$  comparable):

$\tilde{\kappa}$	$\tilde{\lambda}$	$\beta_p$
1.343	0.157	0.038
(1.310)	(0.076)	(0.051)



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# Part II: Which findings should be published?

## Reforming scientific publishing

- Publication bias motivates calls for reform:  
Publication should not select on findings.
  - De-emphasize statistical significance, ban “stars.”
  - Pre-analysis plans to avoid selective reporting of findings.
  - Registered reports reviewed and accepted prior to data collection.
- But: Is eliminating bias the right objective?  
How does it relate to informing decision makers?
- We characterize **optimal publication rules from an instrumental perspective**:
  - Study might inform the public about some state of the world.
  - Then the public chooses a policy action.
  - Take as given that not all findings get published (prominently).

# Which findings should be published?

## Key results

1. **Optimal** rules selectively **publish surprising findings**.  
In leading examples: Similar to two-sided or one sided tests.
2. But: Selective publication **always distorts inference**.  
There is a trade-off policy relevance vs. statistical credibility.
3. With **dynamics**: Additionally publish **precise null** results.
4. With **incentives**: Modify publication rule to **encourage more precise** studies.

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- II Which findings should be published?
  - 1 **Setup and optimal publication rules**
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# Setup

## Timeline and notation

State of the world (parameter)	$\theta$
Common prior	$\theta \sim \pi_0$
<b>Study might be submitted</b>	
Exogenous submission probability	$q$
Design (e.g., standard error)	$S \perp \theta$
Findings (estimate)	$X \theta, S^2 \sim f_{X \theta, S}$
<b>Journal decides whether to publish</b>	$D \in \{0, 1\}$
Publication probability	$p(X, S)$
Publication cost	$c$
Public updates beliefs	$\pi_1 = \pi_1^{(X, S)}$ if $D = 1$ $\pi_1 = \pi_1^0$ if $D = 0$
<b>Public chooses policy action</b>	$a = a^*(\pi_1) \in \mathbb{R}$
Utility	$U(a, \theta)$
Social welfare	$U(a, \theta) - Dc$

# Setup

## Comparison to setup of Part I

- New layer: Belief updating and policy decision by the public.
- Consider only one study here, that might or might not be published.  $\Rightarrow$ 
  - Omit  $*$  notation.
  - $\theta$  is like previous  $\Theta^*$ .
  - $S$  is like previous  $\sigma^*$ .
- Changes of interpretation:
  - $\pi_0$  is a prior, rather than a distribution across studies.
  - $S$  might include sources of uncertainty in addition to sampling variation. Internal and external validity!
  - A special case of  $f_{X|\theta,S}$  is  $N(\theta, S^2)$ .

# Baseline model

## Belief updating and policy decision

- Public belief when study is published:  $\pi_1^{(X,S)}$ .
  - Bayes posterior after observing  $(X, S)$ .
  - Same as journal's belief when study is submitted.
- Public belief when no study is published:  $\pi_1^0$ .

Two alternative scenarios:

  1. Naive updating:  $\pi_1^0 = \pi_0$ .
  2. Bayes updating:  $\pi_1^0$  is Bayes posterior given no publication.
- Public action  $a = a^*(\pi_1)$ 

maximizes posterior expected welfare,  $\mathbb{E}_{\theta \sim \pi_1}[U(a, \theta)]$ .  
Default action  $a^0 = a^*(\pi_1^0)$ .

# Optimal publication rules

- Coming next: We show that **ex-ante** optimal rules, maximizing expected welfare, are those which **ex-post** publish findings that have a big impact on policy.
- **Interim gross benefit**  $\Delta(\pi, a^0)$  of publishing equals
  - Expected welfare given publication,  $\mathbb{E}_{\theta \sim \pi}[U(a^*(\pi), \theta)]$ ,
  - minus expected welfare of default action,  $\mathbb{E}_{\theta \sim \pi}[U(a^0, \theta)]$ .
- **Interim optimal publication rule:**  
Publish if interim benefit exceeds cost  $c$ .
- Want to maximize **ex-ante expected welfare**:

$$\begin{aligned} EW(p, a^0) = & \mathbb{E}[U(a^0, \theta)] \\ & + q \cdot \mathbb{E} \left[ p(X, S) \cdot (\Delta(\pi_1^{(X, S)}, a^0) - c) \right]. \end{aligned}$$

- Immediate consequence:  
**Optimal policy is interim optimal** given  $a^0$ .



# Optimal publication rules

## Optimality and interim optimality

- Under **naive updating**:
  - Default action  $a^0 = a^*(\pi_0)$  does not depend on  $p$ .
  - **Interim optimal** rule given  $a^0$  is **optimal**.
- Under **Bayes updating**:
  - $a^0$  maximizes  $EW(p, a^0)$  given  $p$ .
  - $p$  maximizes  $EW(p, a^0)$  given  $a^0$ , when interim optimal.
  - These conditions are **necessary but not sufficient** for joint optimality.
- **Commitment does not matter** in our model.
  - Ex-ante optimal is interim optimal.
  - This changes once we consider researcher incentives (endogenous study submission).

## Leading examples

- **Normal prior and signal**, normal posterior:

$$\theta \sim \pi_0 = N(\mu_0, \sigma_0^2)$$

$$X|\theta, S \sim N(\theta, S^2)$$

- **Canonical utility functions:**

1. Quadratic loss utility,  $\mathcal{A} = \mathbb{R}$ :

$$U(a, \theta) = -(a - \theta)^2$$

Optimal policy action:  $a =$  posterior mean.

2. Binary action utility,  $\mathcal{A} = \{0, 1\}$ :

$$U(a, \theta) = a \cdot \theta$$

Optimal policy action:  $a = 1$  iff posterior mean is positive.

# Leading examples

## Interim optimal rules

- Quadratic loss utility: “**Two-sided test.**” Publish if

$$\left| \mu_1^{(X,S)} - a^0 \right| \geq \sqrt{c}.$$

- Binary action utility: “**One-sided test.**” Publish if

$$a^0 = 0 \text{ and } \mu_1^{(X,S)} \geq c, \quad \text{or}$$

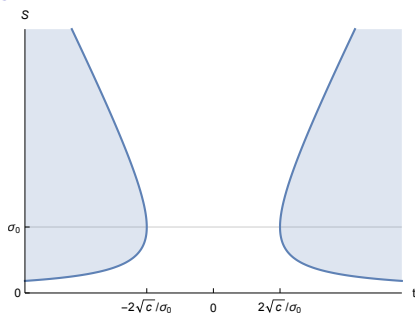
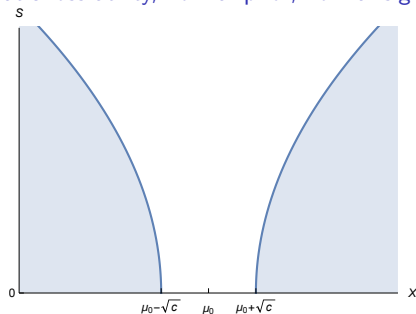
$$a^0 = 1 \text{ and } \mu_1^{(X,S)} \leq -c.$$

- Normal prior and signals:

$$\mu_1^{(X,S)} = \frac{\sigma_0^2}{S^2 + \sigma_0^2} X + \frac{S^2}{S^2 + \sigma_0^2} \mu_0.$$

# Leading examples

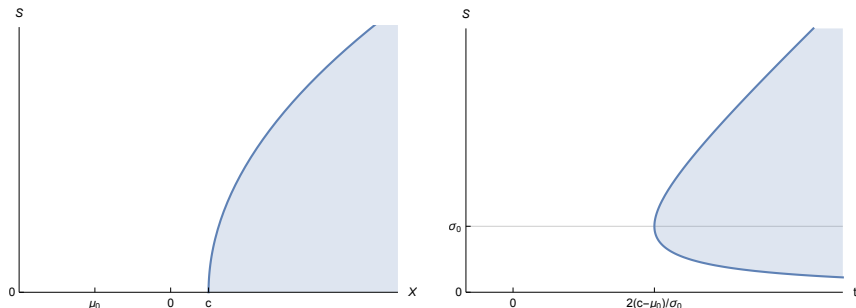
Quadratic loss utility, normal prior, normal signals



- Optimal publication region (shaded). Axes:
  - left Estimate  $X$ , standard error  $S$ .  
(As in meta-studies plots!)
  - right “t-statistic”  $t = (X - \mu_0)/S$ , standard error  $S$ .
- Note:
  - Given  $S$ , publish outside symmetric interval around  $\mu_0$ .
  - Critical value for t-statistic is non-monotonic in  $S$ .

# Leading examples

Binary action utility, normal prior, normal signals



- Optimal publication region (shaded). Axes:
  - left Estimate  $X$ , standard error  $S$ .
  - right “t-statistic”  $t = (X - \mu_0)/S$ , standard error  $S$ .
- Note:
  - When prior mean is negative, optimal rule publishes for large enough positive  $X$ .

# Generalizing beyond these examples

Two key results that generalize:

- **Don't publish null results:**

A finding that induces  $a^*(\pi') = a^0 = a^*(\pi_1^0)$  always has 0 interim benefit and should never get published.

- **Publish findings outside interval:**

Suppose

- $U$  is supermodular.
- $f_{X|\theta,S}$  satisfies monotone likelihood ratio property given  $S = s$ .
- Updating is either naive or Bayes.

Then there exists an interval  $I^s \subseteq \mathbb{R}$  such that  $(X, s)$  is published under the optimal rule if and only if  $X \notin I^s$ .

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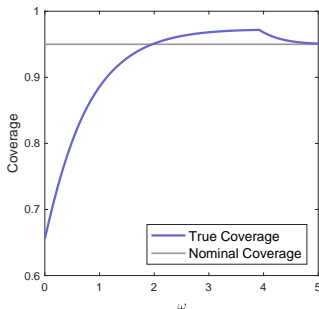
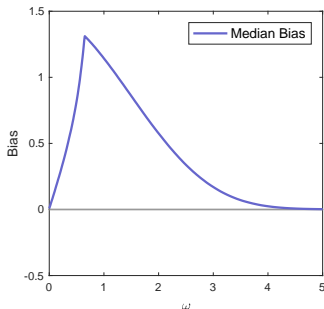
# Selective publication and inference

- Just showed:  
**Optimal publication rules select on findings.**
- But: Selective publication rules can distort inference.
- We show a stronger result:  
Any selective publication rule distorts inference.
- Put differently:  
**If we desire that standard inference be valid, then the publication rule must not select on findings at all.**



# Recall: Publication bias

Example: Selection on significance



- Publication probability: “significance testing,”

$$p(z) = \begin{cases} 0.1 & |z| < 1.96 \\ 1 & |z| \geq 1.96 \end{cases}$$

left median bias of  $\hat{\omega} = Z$

right true coverage of conventional 95% confidence interval

# Selective publication and inference

Validity of inference is equivalent to no selection

For normal signals and prior support with non-empty interior,  
**the following statements are equivalent:**

1. Non-selective publication.  
 $p(x, s)$  is constant in  $x$  for each  $s$ .
2. Publication probability constant in state.  
 $\mathbb{E}[p(X, S) | \theta, S = s]$  is constant over  $\theta \in \Theta_0$  for each  $s$ .
3. Frequentist unbiasedness.  
 $\mathbb{E}[X | \theta, S = s, D = 1] = \theta$  for  $\theta \in \Theta_0$  and for all  $s$ .
4. Bayesian validity of naive updating.  
For all distributions  $F_S$ , the Bayesian default belief  $\pi_1^0$  is equal to the prior  $\pi_0$ .

# Selective publication and inference

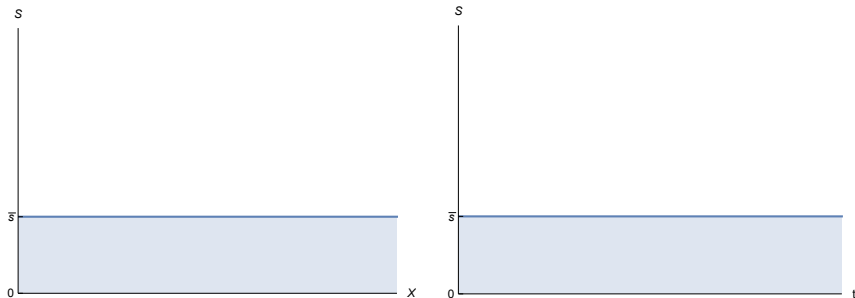
## Intuition and implications

- Sketch of proof:
  - Non-selective publication  $\Rightarrow$  the other conditions: immediate.
  - Constant publication probability  $\Rightarrow$  non-selective publication: Completeness of the normal location family.
  - Unbiasedness  $\Rightarrow$  constant publication probability: “Tweedie’s formula” and integration.
- **Optimal publication if we require non-selectivity?**
- Suppose
  - There are normal signals.
  - Updating is either naive or Bayesian.
  - The publication rule is restricted to not select on  $X$ .

Then there exists  $\bar{s} \geq 0$  for which the optimal rule **publishes** a study **if and only if**  $S \leq \bar{s}$ .

# Selective publication and inference

Optimal non-selective publication region



- For quadratic loss utility, normal prior, normal signals.
- Subject to the constraint that  $p(x, s)$  is restricted to not depend on  $x$ .

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  - a Replication studies
  - b Meta-studies
- 3 Application: Lab experiments in economics

## II Which findings should be published?

- 1 Setup and optimal publication rules
- 2 Selective publication and statistical inference
- 3 **Extensions**
  - a Dynamic model
  - b Researcher incentives

Conclusion

## A dynamic two-period model

- Period 1 as before, with study  $(X_1, S_1)$ , action  $a_1 = a^*(\pi_1)$ .
- Now additionally: Period 2 study, always published.
- Independent estimate

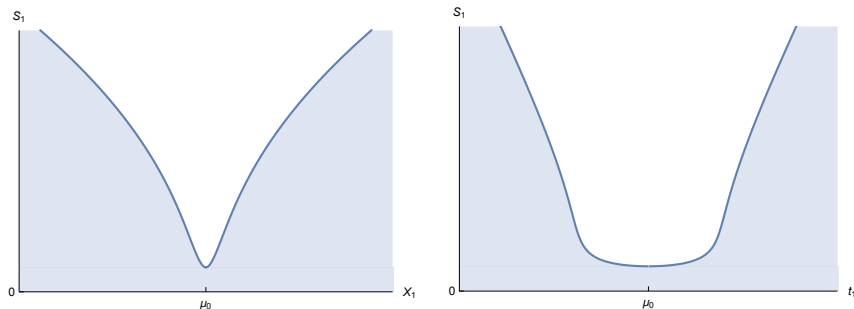
$$X_2 | \theta, X_1, S_1 \sim F_{X_2 | \theta}.$$

- Period 2 action  $a_2 = a^*(\pi_2)$ .
- Social welfare

$$\alpha U(a_1, \theta) - Dc + (1 - \alpha) U(a_2, \theta).$$

# A dynamic two-period model

Quadratic loss utility, normal prior, normal signals, naive updating



- Optimal publication region (shaded).
- Note:
  - For  $S$  small enough, publish even when  $X = \mu_0$ .

# A dynamic two-period model

## General implications

- More generally, for normal signals:
  1. The benefit of publication is strictly positive whenever  $\pi_1^I \neq \pi_1^0$ .
  2. The benefit goes to 0 as either  $s_2 \rightarrow 0$  or  $s_2 \rightarrow \infty$ .
- Put differently:
  1. **Null results** (= prior mean) **that improve precision** are valuable to **prevent future mistakes**.
  2. This value disappears for
    - a) very precise future information (won't make any mistakes either way), and
    - b) very imprecise future information (effectively back to one-period case).



# Researcher Incentives

- Thus far: study submission and design exogenous, random.
- Assume now that a researcher
  1. decides whether or not to submit a study,
  2. and picks a design  $S$ .
- Normal signals with standard error  $S$ .
- Researcher utility:
  1. Utility 1 from getting published,
  2. cost  $\kappa(S)$  depending on design  $S$ .
- Expected researcher utility

$$E_{\theta \sim \pi_0, X \sim N(\theta, S^2)}[p(X, S)] - \kappa(S).$$

- Outside option with utility 0.
- Journal faces
  1. participation constraint (PC) and
  2. incentive compatibility constraint (ICC).

# Researcher Incentives

## Constrained optimal rule

- Journal objective as before,  $U(a, \theta) - Dc$ .
- Journal commits to publication rule  $p(x, s)$  ex-ante.  
Commitment matters in this extension!
- Optimal publication rule subject to (PC) and (ICC)?
- Solution: Relative to baseline model, journal **distorts publication rule** in two ways
  - Reject imprecise studies (large  $S$ ) – even if valuable ex post.
  - For low enough  $S$ , set interim benefit threshold for acceptance below  $c$ .

# Conclusion

## Key findings

- I Which findings get published?
  - 1 If form and magnitude of selection are known, we can correct published findings.
  - 2 Form and magnitude of selection are nonparametrically identified.
  - 3 Published research is selected.
- II Which findings should be published?
  - 1 Optimal rules selectively publish surprising findings.  
In leading examples: Similar to two-sided or one sided tests.
  - 2 But: Selective publication always distorts inference.  
There is a trade-off policy relevance vs. statistical credibility.
  - 3 With dynamics: Additionally publish precise null results.
  - 4 With incentives: Modify publication rule to encourage more precise studies.

# Conclusion

## Outlook

Different ways of thinking about statistics / econometrics:

1. Making decisions based on data.
  - Objective function?
  - Set of feasible actions?
  - Prior information?
2. Statistics as (optimal) communication.
  - Not just “you and the data.”
  - What do we communicate to whom?
  - Subject to what costs and benefits?  
Why not publish everything? Attention?
3. Statistics / research as a social process.
  - Researchers, editors and referees, policymakers.
  - Incentives, information, strategic behavior.
  - Social learning, paradigm changes.

**Much to be done!**

A web-app for estimating publication bias in meta-studies is available at

<https://maxkasy.github.io/home/metastudy/>

Thank you!