Identification of and correction for publication bias

Isaiah Andrews    Maximilian Kasy
Introduction

- Fundamental requirement of science: replicability.
- Different researchers should reach same conclusions.
- Methodological conventions should ensure this.
  (e.g., randomized experiments)
- Despite restrictive methodology, replicability often appears to fail:
  - Experimental economics (Camerer et al., 2016),
  - Experimental psychology (Open Science Collaboration, 2015),
  - Medicine (Ionnidias, 2005),
  - Cell Biology (Begley et al, 2012),
  - Neuroscience (Button et al, 2013),
  - ...
Possible explanation: selective publication of results.

Due to:
- Researcher specification search
- Journal selectivity

Possible selection criteria:
- Statistically significant effects
- Confirmation of prior beliefs
- Novelty
- ...

Consequences:
- Conventional estimators are biased
- Conventional inference does not control size
“Replication crisis” got media attention

Last week tonight, May 8 2016
Our contributions

1. Nonparametric identification of selectivity in the publication process, using
   a) Replication studies: Absent selectivity, original and replication estimates should be symmetrically distributed.
   b) Meta studies: Absent selectivity, distribution of estimates for small sample sizes should be noised-up version of distribution for larger sample sizes.

2. Corrected inference when selectivity is known
   a) Median unbiased estimators.
   b) Confidence sets with correct coverage.
   c) Allow for nuisance parameters and multiple dimensions of selection.

3. Applications to
   a) Experimental economics.
   b) Experimental psychology.
   c) Effects of minimum wages on employment.
   d) Effects of de-worming.
Roadmap

- Literature
- Setup
- Identification of selectivity
  1. Using replication studies
  2. Using meta-studies
- Corrected inference
- Empirical applications
- Conclusion
Identification of publication bias:

- Good overview:
  Rothstein et al. (2006)

- Regression based:
  Egger et al. (1997)

- Symmetry of funnel plot (“trim and fill”):
  Duval and Tweedie (2000)

- Parametric selection models:

- Distribution of p-values, parametric distribution of true effects:
  Brodeur et al. (2016)
Corrected inference:
▶ McCrary et al. (2016)

Replication- and meta-studies for empirical part:
▶ Replication of econ experiments: Camerer et al. (2016)
▶ Replication of psych experiments: Open Science Collaboration (2015)
▶ Minimum wages: Wolfson and Belman (2015)
▶ Deworming: Croke et al. (2016)
General setup

- Assume that there are studies $i$, which might or might not get published (due to researcher or journal selectivity).
- Each study reports findings $X_i^*$ with a distribution governed by $\Theta_i^*$.
- $\Theta_i^*$ drawn from some population $\Rightarrow$ empirical Bayes perspective.
- Probability of publication $P(D_i = 1) = p(X_i^*)$.
- Key question: do we know of existence of specific unpublished studies?
  1. No? $\Rightarrow$ truncation (we will assume this).
  2. Yes? $\Rightarrow$ censoring.
- Published studies are indexed by $j$. 
Example: treatment effects

- Journal receives a stream of studies $i = 1, 2, \ldots$
- Each reporting experimental estimates $X_i^*$ of treatment effects $\Theta_i^*$.
- Distribution of $\Theta_i^*$: $\pi$.
- Suppose that $X_i^* | \Theta_i^* \sim N(\Theta_i^*, 1)$.
- Publication probability: “significance testing,”

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

- Published studies: report estimate $X_j$ of treatment effect $\Theta_j$.
Example continued – Publication bias

- Left: median bias of $\hat{\theta}_j = X_j$.
- Right: true coverage of conventional 95% confidence interval.
Definition (General sampling process)

Latent (unobserved) variables: \((D_i, X_i^*, \Theta_i^*)\), jointly i.i.d. across \(i\)

\[\Theta_i^* \sim \mu\]
\[X_i^* | \Theta_i^* \sim f_{X^*|\Theta^*}(x | \Theta_i^*)\]
\[D_i | X_i^*, \Theta_i^* \sim Ber(p(X_i^*))\].

**Truncation:** We observe i.i.d. draws of \(X_j\), where
\[l_j = \min\{i : D_i = 1, i > l_{j-1}\}\]
\[\Theta_j = \Theta_{l_j}^*\]
\[X_j = X_{l_j}^*\].
Lemma (Likelihood)

The sampling process of definition 1 implies the following likelihood:

\[ f_{X|\Theta}(x|\theta) = \frac{p(x)}{E[p(X_i^*)|\Theta_i^* = \theta]} f_{X_i^*|\Theta_i^*}(x|\theta). \]
Identification of the selection mechanism $p(.)$

- How would we know whether selectivity is present?
- We propose two approaches for identification:
  1. Replication experiments:
     - replication estimate $X'$ for the same parameter $\Theta$
     - selectivity operates only on $X$, but not on $X'$
  2. Meta-studies:
     - variation in $\sigma^2$, where $X^* \sim N(\Theta^*, \sigma^2)$
     - assume variation of $\sigma^2$ is (conditionally) independent of the
       variation of $\Theta$ across studies
       (standard assumption in the meta-studies literature;
       validated in our applications by comparison to replications)
- Advantages:
  1. Replications: Very credible.
Intuition: identification using replication studies

- Left: no truncation
  ⇒ areas A and B have same probability.

- Right: \( p(X) = 0.1 + 0.9 \cdot 1(|X| > 1.96) \)
  ⇒ A more likely then B.
Intuition: identification using meta-studies

- Left: no truncation
  \[ \Rightarrow \text{dist for higher } \sigma \text{ noised up version of dist for lower } \sigma. \]

- Right: \( p(X) = 0.1 + 0.9 \cdot 1(|X| > 1.96) \)
  \[ \Rightarrow \text{“missing data” inside the cone.} \]
Approach 1: Replication studies

Definition (Replication sampling process)

- **Latent variables:** as before,
  \[ \Theta_i^* \sim \mu \]
  \[ X_i^* | \Theta_i^* \sim f_{X^* | \Theta^*}(x | \Theta_i^*) \]
  \[ D_i | X_i^*, \Theta_i^* \sim Ber(p(X_i^*)) \]

- **Additionally:** Replication draws,
  \[ X_i^{*r} | X_i^*, D_i, \Theta_i^* \sim f_{X^* | \Theta^*}(x | \Theta_i^*) \]

- **Observability:** as before,
  \[ l_j = \min\{i : D_i = 1, \ i > l_{j-1}\} \]
  \[ \Theta_j = \Theta_{l_j} \]
  \[ (X_j, X_{j}^{r}) = (X_{l_j}^*, X_{l_j}^{*r}) \].
The marginal (empirical Bayes) density of \((X, X')\) is given by

\[
f_{X, X'}(x, x') = \frac{p(x)}{E[p(X_i^*)]} \int f_{X^*|\Theta^*}(x | \theta_i^*) f_{X^*|\Theta^*}(x' | \theta_i^*) d\mu(\theta_i^*).
\]

Note:

- \(f_{X^*, X'^*}\) is symmetric in its arguments.
- \(f_{X, X'}\) is asymmetric because of \(p(x)\).
Theorem (Identification using replication experiments)

Assume that the support of \( f_{x^*_i, x^*_r} \) is of the form \( A \times A \) for some measurable set \( A \).
Then \( p(\cdot) \) is identified on \( A \) up to scale.

Proof:

- For all \( a, b \),

\[
f_{x, x^r}(a, b) \cdot p(b) = f_{x, x^r}(b, a) \cdot p(a).
\]

- Let \( (a, b) \in A \times A \) s.t. \( f_{x, x^r}(a, b) > 0 \), in particular \( p(a) > 0 \).

\[
\Rightarrow f_{x, x^r}(a, c) > 0 \text{ for all } c \in A \Rightarrow
\]

\[
p(c) = p(a) \cdot \frac{f_{x, x^r}(c, a)}{f_{x, x^r}(a, c)}
\]

for all \( c \in A \). \( \square \)
Practical complication

- Replication experiments follow the same protocol ⇒ estimate same effect $\Theta$.
- But often different sample size ⇒ different variance ⇒ symmetry breaks down.
- Additionally: Replication sample size often determined based on power calculations given initial estimate.

\[
\Theta_i^* \sim \mu \\
Z_i^* | \Theta_i^* \sim N(\Theta_i^*, 1) \\
D_i | Z_i^*, \Theta_i^* \sim Ber(p(Z_i^*)) \\
\sigma_i | D_i, Z_i^*, \Theta_i^* \sim f_{\sigma|Z^*} \\
Z_i^{*r} | \sigma_i, D_i, Z_i^*, \Theta_i^* \sim N(\Theta_i^*, \sigma_i^2). 
\]
Corollary

*In this setup* $p(\cdot)$ *is identified on* $\mathbb{R}$ *up to scale.*

**Sketch of proof:**
Conditional on $Z, \sigma,$ (de-)convolve $Z_j'$ with normal noise to get symmetry back. □
Likelihood for estimation

- Truncated marginal likelihood:

\[
f_{Z,Z^r,\sigma}(z,z^r,\sigma) = \frac{p(z)}{\int p(z') \cdot \varphi(z' - \theta) dz' d\mu(\theta)} \cdot f_{\sigma|Z^*}(\sigma|z) \cdot \int \varphi(z - \theta) \cdot \frac{1}{\sigma} \varphi \left( \frac{z^r - \theta}{\sigma} \right) d\mu(\theta).
\]

- Use this for maximum likelihood estimation, with parametric models for \( \mu, p(\cdot) \).

- For instance,

\[
\Theta^* \sim N(\bar{\theta}, \tau^2)
\]

\[
p(Z) = 1(|Z| \geq 1.96) + \beta_p \cdot 1(|Z| < 1.96).
\]
Further complication

- What if selectivity is based not only on observed $Z$, but also on unobserved $W$?
- Would imply general selectivity of the form
  \[
  D_i | Z^*, \Theta^*_i \sim \text{Ber}(p(Z^*_i, \Theta^*_i)).
  \]
- Assume again normality,
  \[
  Z^*_r | \sigma_i, D_i, Z^*_i, \Theta^*_i \sim N(\Theta^*_i, \sigma_i^2).
  \]
- ⇒ Solution:
  - Identify $\mu_{\Theta | Z}$ from $f_{Z^r | Z}$ by deconvolution.
  - Recover $f_{Z | \Theta}$ by Bayes’ formula ($f_Z$ is observed).
  - This density is all we need for bias corrected inference!
- Our applications assume selection on observed $Z$, for now.
Approach 2: Meta-studies

Definition (Independent $\sigma$ sampling process)

\[
\begin{align*}
\sigma^*_i & \sim \mu_\sigma \\
\Theta^*_i | \sigma^*_i & \sim \mu_\Theta \\
X^*_i | \Theta^*_i, \sigma^*_i & \sim N(\Theta^*_i, \sigma^*_i^2) \\
D_i | X^*_i, \Theta^*_i, \sigma^*_i & \sim Ber(p(X^*_i / \sigma^*_i)).
\end{align*}
\]

We observe i.i.d. draws of $(X_j, \sigma_j)$, where

\[
l_j = \min\{ i : D_i = 1, \ i > l_{j-1} \}
\]

$(X_j, \sigma_j) = (X^*_{l_j}, \sigma^*_{l_j})$.

Define $Z^* = \frac{X^*}{\sigma^*}$ and $Z = \frac{X}{\sigma}$.
Theorem (Nonparametric identification using variation in $\sigma$, independent effects)

Consider the setup for meta-studies of Definition 3. Suppose that the support of $\sigma$ contains a neighborhood of $\sigma_0$. Then $p(\cdot)$ is identified up to scale.

Proof:

- W.l.o.g. $\sigma_0 = 1$, $h(z) := f_{Z^*|\sigma^*}(z|1)$.

- $f_{Z|\sigma}(z|\sigma) = \frac{p(z)}{E[p(Z^*)|\sigma]} f_{Z^*|\sigma^*}(z|\sigma)$ and thus

$$p(z) = \text{const.} \cdot \frac{f_{Z|\sigma}(z|1)}{h(z)}.$$

- We will show that $h(\cdot)$ is identified.
Let
\[ g(z) := \partial_\sigma \log f_{Z|\sigma}(z|1) = C_1 + \partial_\sigma \log f_{Z^*|\sigma^*}(z|1) \]

- \( g \) is identified because \( f_{Z|\sigma} \) is observed.
- Given our model assumptions, for \( \sigma > 1 \)

\[ f_{Z^*|\sigma^*}(z|\sigma) = \sigma \int \varphi(\eta) h(\sigma z + (1 - \sigma)\eta) d\eta. \]

- Thus
\[ g(z) - C_1 = \partial_\sigma \log f_{Z^*|\sigma^*}(z|1) = 1 + z \frac{h'(z)}{h(z)}. \]

- Consider \( z = 0 \Rightarrow C_1 = g(0) - 1. \)
- Thus
\[ (\log h(z))' = \frac{h'(z)}{h(z)} = \frac{g(z) - g(0)}{z}. \]

- Integrate, exponentiate, normalize \( \int h = 1 \) to recover \( h \) itself. □
likelihood for estimation

▶ Assume that

\[ \Theta^* \sim \mathcal{N}(\bar{\theta}, \tau^2) \]

with \( \bar{\theta} \) and \( \tau^2 \) unknown.

▶ \( \Rightarrow \) truncated marginal likelihood given \( \sigma \):

\[
f_{X|\sigma}(x|s) = \frac{p(x/s)}{\int p(x'/s)\varphi_{\sqrt{s^2+\tau^2}}(x' - \bar{\theta})dx'} \cdot \varphi_{\sqrt{s^2+\tau^2}}(x - \bar{\theta}).
\]

▶ Use this for maximum likelihood estimation, with parametric models for \( p(\cdot) \).
Bias-corrected inference

- Assume $X$, $\Theta$ both 1-dimensional.
- Ex ante publication probability given $\Theta^*$:
  
  $$E[p(X^*)|\Theta^* = \theta^*].$$

- Density of published $X$ given $\Theta$:
  
  $$f_{X|\Theta}(x|\theta) = \frac{p(x)}{E[p(X^*)|\theta^*]} \cdot f_{X^*|\Theta^*}(x|\theta).$$

- Corresponding cumulative distribution function: $F_{X|\Theta}(x|\theta)$.
  
  - Assume strict monotonicity, continuity in $\theta$.
  - Holds in normal model.
Corrected estimators and confidence sets

- We are interested in bias, and the coverage of confidence sets.
  - Condition on $\theta$: standard frequentist analysis.
- Define $\hat{\theta}_\alpha (x)$ via
  \[ F_{X|\Theta} \left( x | \hat{\theta}_\alpha (x) \right) = \alpha. \]
- By quantile inversion:
  \[ P \left( \hat{\theta}_\alpha (X) \leq \theta | \theta \right) = \alpha. \]
- Median-unbiased estimator: $\hat{\theta}_{\frac{1}{2}} (X)$ for $\theta$.
- Equal-tailed level $1 - \alpha$ confidence interval:
  \[ \left[ \hat{\theta}_{\frac{\alpha}{2}} (X), \hat{\theta}_{1-\frac{\alpha}{2}} (X) \right]. \]
Example: treatment effects

- Let us return to the treatment effect example discussed above.
- Assume $X^*|\Theta^* \sim N(\Theta^*, 1)$ and

$$p(X) = 1 + (\beta_p - 1) \cdot 1(|X| < 1.96).$$

- Ex ante publication probability given $\Theta^*$:

$$E[p(X^*)|\Theta^* = \theta^*] = 1 + (\beta_p - 1) \cdot (\Phi(1.96 - \theta^*) - \Phi(-1.96 - \theta^*)) .$$

- $f_{X|\Theta}$ and $F_{X|\Theta}$ are available in closed form, $\hat{\theta}_\alpha$ easy to compute.
  - Same holds more generally provided $p(\cdot)$ is a step function.
Example continued – corrected confidence sets for $\beta_p = .1$
Frequentist inference with multivariate $X$

- Problem more involved for multivariate $X$.
- Suppose full parameter is $\theta_i^*$,

$$X_i^* | \theta_i^* \sim \mathcal{N}(\theta_i^*, \Sigma_i^*).$$

with $\Sigma_i^*$ observed whenever $X_i^*$ is observed.

- We are interested in inference on $\gamma = v' \theta$ for known $v$.
- Sample analog: $G = v' X$. 

Publication bias

- Bias-corrected inference
Example: Difference in Differences

- Pretesting for parallel trends common in difference in differences.
- Consider a simple example with two states $s$, three time periods $t$, and independence and homoskedasticity across $(s, t)$ pairs.
- For $W$ estimated violation of parallel trends, $G$ difference in differences estimate, and $\sigma$ the variance of state-time means,

\[
\begin{pmatrix}
W \\
G
\end{pmatrix}
\sim N\left(\begin{pmatrix}
\omega \\
\gamma
\end{pmatrix}, \begin{pmatrix}
2\sigma & -2\sigma \\
-2\sigma & 4\sigma
\end{pmatrix}\right)
\]

where $\omega = 0$ under parallel trends.

- Consider screening on both $W$ and $G$:

\[p(X) = (0.1)^1\{W/\sigma_W \geq 1.96\} + 1\{G/\sigma_G < 1.96\}\]
Example: Bias in Difference in Differences
Conditioning

- Components of $\theta$ other than $\gamma$ are nuisance parameters.
  - Not of direct interest, but can affect publication probability and thus inference.
- Truncation preserves exponential family structure, so we can condition out the nuisance parameter.
  - In fact, truncation preserves sufficient statistics, and sufficient statistic $W$ is a one-to-one transformation of $\left( I - \frac{\Sigma v v'}{v' \Sigma v} \right) X$.
  - Complete sufficient statistic for nuisance parameter

$$\omega = \left( I - \frac{\Sigma v v'}{v' \Sigma v} \right) \theta.$$
Conditional density

- By sufficiency, the conditional distribution of \( G \mid W, \gamma, \omega \) does not depend on \( \omega \).
- Conditional density and distribution function available in closed form if \( p(\cdot) \) is a step function constant on polyhedra.
  - Uses result from Lee et al. (2014).
- To construct quantile-unbiased estimators, repeat previous analysis conditional on \( W \).
- Can again construct median-unbiased estimates and equal-tailed confidence intervals.
Optimality

- Using results from Pfanzagl (1994), we show that $\hat{\gamma}_\alpha (X)$ is optimal (among quantile-unbiased estimators) in a strong sense.
- Let $L(d, \gamma)$ be any quasi-convex loss function that attains its minimum at $d = \gamma$.
- For any other level-$\alpha$ quantile unbiased estimator $\tilde{\gamma}_\alpha (X)$,

\[ E [L(\hat{\gamma}_\alpha (X), \gamma) | (\gamma, \omega)] \leq E [L(\tilde{\gamma}_\alpha (X), \gamma) | (\gamma, \omega)] \]

for all $(\gamma, \omega)$. 
Example: Bias in Difference in Differences
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.
- Replications: public predefined analysis plans.
- Statistical power of at least 90% to detect the original effect size at the 5% level.
- Scatterplot next slide:
  - $Z = X / \sigma$: normalized initial estimate
  - $Z^r = X^r / \sigma$: replicate estimate
Publication bias

Applications
Estimates of selection model

• Model:

\[ \Theta^* \sim N(\bar{\theta}, \tau^2) \]

\[ p(Z) = \begin{cases} 
\beta_p & |Z| < 1.96 \\
1 & |Z| \geq 1.96 
\end{cases} \]

• Estimates:

<table>
<thead>
<tr>
<th>\tau</th>
<th>\beta_p</th>
</tr>
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<tbody>
<tr>
<td>2.354</td>
<td>0.100</td>
</tr>
<tr>
<td>(0.751)</td>
<td>(0.091)</td>
</tr>
</tbody>
</table>
Publication bias

Applications

Lab experiments in economics, adjusted original estimates

Kuziemko et al. (QJE 2014)
Ambrus and Greiner (AER 2012)
Abeler et al. (AER 2011)
Chen and Chen (AER 2011)
Ilcher and Zarghamee (AER 2011)
Ericson and Fuster (QJE 2011)
Ilcher and Zarghamee (AER 2011)
Chen and Chen (AER 2011)
Abeler et al. (AER 2011)
Ambrus and Greiner (AER 2012)
Kuziemko et al. (QJE 2014)
Publication bias

Applications

Kuziemko et al. (QJE 2014)
Ambrus and Greiner (AER 2012)
Abeler et al. (AER 2011)
Chen and Chen (AER 2011)
Ifcher and Zarghamee (AER 2011)
Ericson and Fuster (QJE 2011)
Kirchler et al (AER 2012)
Fehr et al. (AER 2013)
Duffy and Puzzello (AER 2014)
Charness and Dufwenberg (AER 2011)
Huck et al. (AER 2011)
Bartling et al. (AER 2012)
Dulleck et al. (AER 2011)
Kogan et al. (AER 2011)
Fudenberg et al. (AER 2012)
de Clippel et al. (AER 2014)
Friedman and Oprea (AER 2012)
Kessler and Roth (AER 2012)

Original Estimates
Adjusted Estimates
Replication Estimates
Lab experiments in economics, meta-studies approach
Estimates of meta-studies selection model

- Model:

\[ \tilde{\Theta}^* \sim N(\tilde{\theta}, \tilde{\tau}^2) \]

\[ p(X) = \begin{cases} 
\beta_p & |X/\sigma| < 1.96 \\
1 & |X/\sigma| \geq 1.96 
\end{cases} \]

- Recall replication-based estimates:

\[
\begin{array}{c|c}
\tau & \beta_p \\
2.354 & 0.100 \\
(0.751) & (0.091)
\end{array}
\]

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

\[
\begin{array}{c|c}
\tilde{\tau} & \beta_p \\
1.475 & 0.045 \\
(0.362) & (0.045)
\end{array}
\]
Replications of lab experiments in psychology

- 270 contributing authors.
- Sample: 100 out of 488 articles published 2008 in
  - Psychological Science,
  - Journal of Personality and Social Psychology,
- Experimental and correlational studies.
- Some critiques by Gilbert et al. (2016):
  - statistical misinterpretation,
  - not all replication protocols endorsed by original authors.
    ⇒ we re-run estimators on subset of approved replications.
Publication bias

Applications
Estimates of selection model

Model:

\[ \Theta^* \sim N(\bar{\theta}, \tau^2) \]

\[ p(X) = \begin{cases} 
\beta_{p_1} & |Z| < 1.96 \\
\beta_{p_2} & 1.96 \leq |Z| < 2.58 \\
1 & |Z| \geq 2.58 
\end{cases} \]

Estimates:

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<td>(0.208)</td>
<td>(0.018)</td>
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Lab experiments in psychology, meta-studies approach
Estimates of meta-studies selection model

- Model:
  \[ \tilde{\Theta}^* \sim \mathcal{N}(\tilde{\theta}, \tilde{\tau}^2) \]

\[
p(X) = \begin{cases} 
\beta_{p1} & |Z| < 1.96 \\
\beta_{p2} & 1.96 \leq |Z| < 2.58 \\
1 & |Z| \geq 2.58 
\end{cases} 
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- Recall replication-based estimates:

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

<table>
<thead>
<tr>
<th>$\tilde{\tau}$</th>
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<tbody>
<tr>
<td>-0.278</td>
<td>0.043</td>
</tr>
<tr>
<td>(0.052)</td>
<td>(0.025)</td>
</tr>
<tr>
<td>0.926</td>
<td>(0.326)</td>
</tr>
</tbody>
</table>
Subset of approved replications

- 67 studies

- Replication-based estimates:

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<tr>
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<td>0.091</td>
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<tr>
<td>(0.311)</td>
<td>(0.050)</td>
</tr>
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- Meta-study based estimates:

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<td>0.108</td>
</tr>
<tr>
<td>(0.052)</td>
<td>(0.070)</td>
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</table>
Meta-study of the effect of minimum wages on employment

- Wolfson and Belman (2015).
- Elasticity of employment w.r.t. the minimum wage. \( X > 0 \Leftrightarrow \) negative employment effect.
- 60 analyses of U.S. data that were published after 2000, either as articles in journals or as working papers.
- For some: more than 1 estimate per study. (in contrast to our model assumptions) \( \Rightarrow \) cluster standard errors at study level
Estimates of selection model

Model:

\[ \Theta^* \sim \mathcal{N}(\bar{\theta}, \tau^2) \]

\[
p(X) = \begin{cases} 
\beta_{p1} & X/\sigma < -1.96 \\
\beta_{p2} & -1.96 \leq X/\sigma < 0 \\
\beta_{p3} & 0 \leq X/\sigma < 1.96 \\
1 & X/\sigma \geq 1.96 
\end{cases}
\]

Estimates:

<table>
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<tr>
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<tr>
<td>-0.186</td>
<td>0.954</td>
<td>0.225</td>
</tr>
<tr>
<td>0.417</td>
<td>0.297</td>
<td>0.424</td>
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<td>(0.417)</td>
<td>(0.297)</td>
<td>(0.120)</td>
</tr>
<tr>
<td>0.738</td>
<td>(0.210)</td>
<td>(0.291)</td>
</tr>
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</table>
Meta-study of the effects of deworming

- Croke et al. (2016).
- Follow procedures outlined in the “Cochrane Handbook for Systematic Reviews of Interventions.”
- Randomized controlled trials of deworming that include child body weight as an outcome.
- 22 estimates from 20 studies.
Estimates of selection model

- Model:

\[ \Theta^* \sim N(\bar{\theta}, \tau^2) \]

\[ p(X) = \begin{cases} 
\beta_p & |X/\sigma| < 1.96 \\
1 & |X/\sigma| \geq 1.96 
\end{cases} \]

- Estimates:

<table>
<thead>
<tr>
<th>\tau</th>
<th>\beta_p</th>
</tr>
</thead>
<tbody>
<tr>
<td>2.374</td>
<td>2.626</td>
</tr>
<tr>
<td>(0.862)</td>
<td>(1.932)</td>
</tr>
</tbody>
</table>
Conclusion

- Selectivity in the publication process is a potentially serious problem for statistical inference.
- We can non-parametrically identify the presence of selectivity:
  - Using replication studies:
    Original and replication estimates would be symmetrically distributed.
    (absent selectivity)
  - Using meta-studies:
    Higher-variance estimates distribution would be noised-up version of lower-variance estimate distribution.
    (absent selectivity, under independence assumption)
Easy correction for selectivity, if form is known:
- Median unbiased estimators.
- Equal-tailed confidence sets with correct coverage.
- Allowing for nuisance parameters (e.g. selectivity on specification checks).

Empirical findings:
- Strong selectivity on significance in experimental economics, experimental psychology.
- Meta-studies approach applied to initial estimates yields very similar results to replication approach!
- Evidence of strong selectivity (toward significant negative effects) in minimum wage literature.
- Selectivity toward insignificant effects in meta-study for de-worming.
Thanks for your time!