

Meta-Analysis Instrumental Variable Estimator (MAIVE)

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Example: meta-analyzing the education premium

True model:

$$Earnings_j = \gamma Education_j + \delta Ability_j + v_j,$$

Ability **not observed**.

Primary studies:

- 1 ignore ability $\rightarrow \hat{\gamma}$ too large, $SE(\hat{\gamma})$ likely too small (ability matters for education).
- 2 include a proxy $\rightarrow \hat{\gamma}$ smaller, $SE(\hat{\gamma})$ likely larger (more collinearity).
- 3 quasi-experiment \rightarrow if done well (e.g., good instrument), $\hat{\gamma}$ even smaller, $SE(\hat{\gamma})$ likely even larger.

Example: meta-analyzing the education premium

Omitted variable:

The diagram shows the regression equation $Earnings_j = \gamma Education_j + w_j$. The coefficient γ is circled in red. Two curved arrows indicate a feedback loop: one arrow starts from the right side of the equation and points to the coefficient γ , and another arrow starts from the right side of the equation and points to the error term w_j .

$$Earnings_j = \gamma Education_j + w_j$$

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Example: meta-analyzing the education premium

Proxy:

$$Earnings_j = \gamma Education_j + \omega IQ_j + x_j,$$

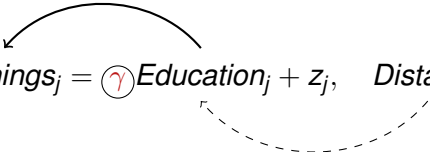

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Example: meta-analyzing the education premium

Instrument:

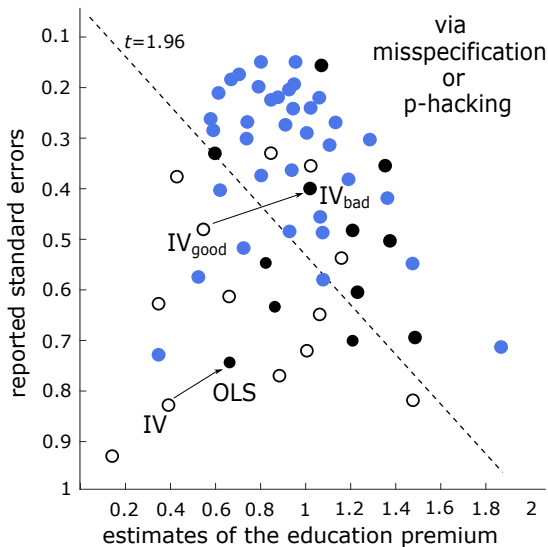
$$Earnings_j = \gamma Education_j + z_j, \quad Distance_j$$


Ability **not observed**.

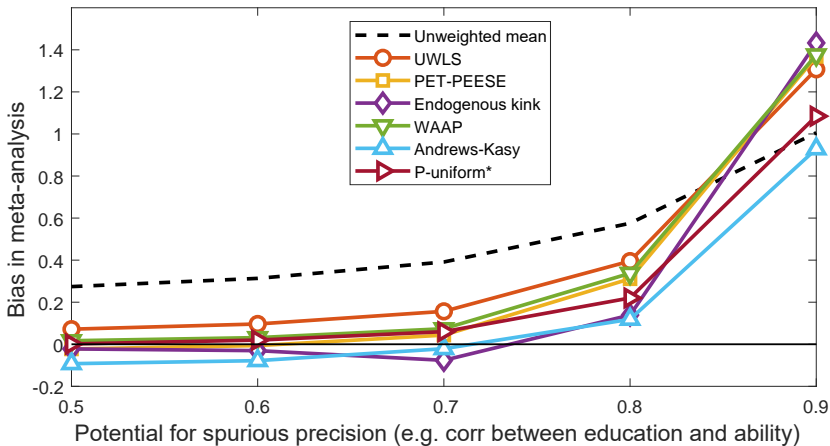
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Some estimates both spuriously large & precise



Simulation: all meta estimators biased upwards



Reason: key meta assumption broken

PEESE:

$$\hat{E}_i = \textcircled{E_0} + \beta SE(\hat{E}_i)^2 + u_i,$$

Methods or p-hacking

Methods or p-hacking

$\text{corr}(SE, u) \neq 0 \Rightarrow \hat{\beta}$ and \hat{E}_0 biased. Problem in all meta estimators (funnel-based, selection models, simple random effects). All of them use SE as a regressor, identification threshold, or weight.

Natural solution: N instrumenting $SE(\hat{E}_i)^2 \rightarrow$ MAIVE.

Options for the meta-analyst

- 1 Use only quasi-experimental studies (ignore those that can be spuriously precise). Is quality binary?
- 2 Include controls in meta-regression (dummies for OLS, DID, ...). Are we sure we are not missing some?

In observational research
we never know the true model!

- 3 Remove “bad” variation from SE → MAIVE.

Meta-analysis instrumental variable estimator

MAIVE intuition:

Definition of SE

$$\hat{E}_i = \textcircled{E_0} + \beta SE(\hat{E}_i)^2 + u_i \cdot 1/N_i$$

- MAIVE + PEESE = classical IV.
- Can add **controls in the 2nd stage** (dummies for OLS, DID, ...).
- You can plug MAIVE-adjusted SEs into other estimators (e.g., do simple random effects with adjusted SEs).

Meta-analysis instrumental variable estimator

MAIVE first stage:

$$SE(\hat{E})_i^2 = \alpha_0 + \alpha_1 (1/N_i) + \pi_i.$$

hacking or misspecifications


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Meta-analysis instrumental variable estimator

MAIVE adjustment:

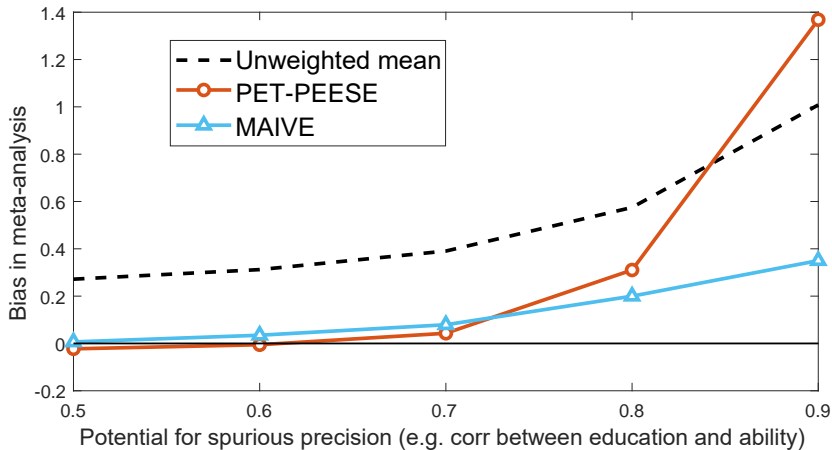
$$SE(\hat{E})_{adj,i}^2 = \hat{\alpha}_0 + \hat{\alpha}_1 (1/N_i) + \pi_i$$

hacking or misspecifications

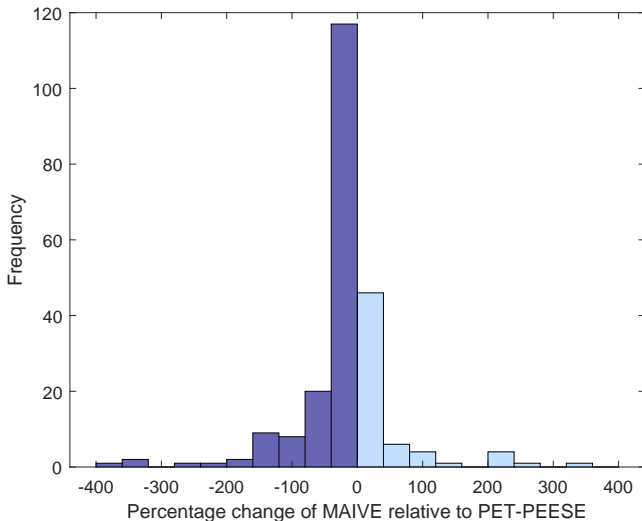


- MAIVE + PEESE = classical IV.
- Can add **controls in the 2nd stage** (dummies for OLS, DID, ...).
- You can plug MAIVE-adjusted SEs into other estimators (e.g., do simple random effects with adjusted SEs).

Simulation: MAIVE alleviates the bias



MAIVE reduces PET-PEESE in most econ metas



Practical issues for a meta-analyst

Main consideration

- Can methods or p-hacking influence both \hat{E} and SE ? Or could there be another relationship between \hat{E} and SE beyond publication bias (e.g. because you use a standardized effect size)?
- Yes \rightarrow MAIVE helps.
- No \rightarrow MAIVE doesn't hurt much (but makes the meta estimate less precise).

Project Website

meta-analysis.cz/maive

Papers using MAIVE

-  Irsova Z., P. Bom, T. Havranek, & H. Rachinger (2024):
Spurious Precision in Meta-Analysis of Observational
Research.
Nature Human Behaviour, 2nd revision.
-  Opatrny M., T. Havranek, Z. Irsova, & M. Scasny (2024):
Publication Bias and Model Uncertainty in Measuring the
Effect of Class Size on Achievement.
Journal of Labor Economics, revise and resubmit.
-  Havranek T., Z. Irsova, & O. Zeynalova (2024):
Publication and Attenuation Biases in Measuring
Skill Substitution.
Review of Economics and Statistics 106(5): 1187-1200.