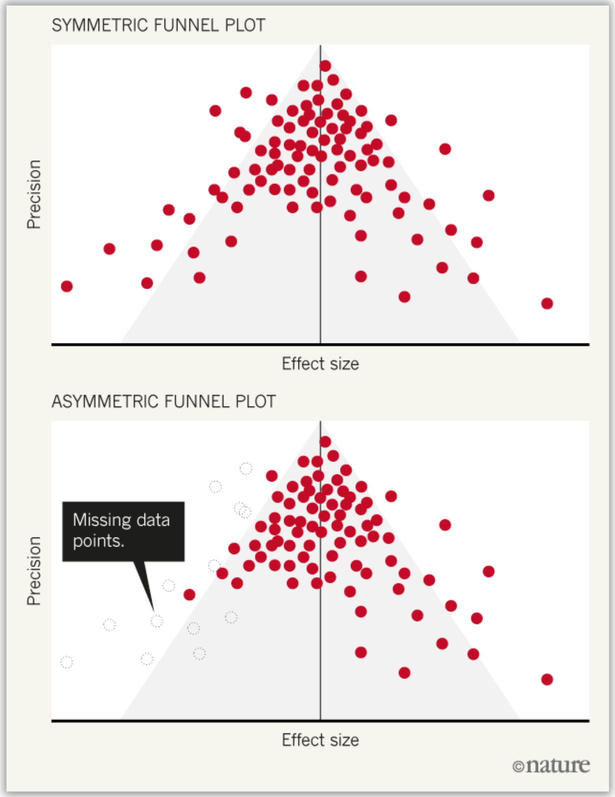
# Small-Study Effect Methods

→ Reporting biases are driven by small studies (i.e., studies with large standard errors)

## Core Assumptions

1. **Large studies** are likely to get published, no matter whether the results are significant or not.
2. **Moderately sized** studies are at greater risk of not being published. However, even when the statistical power is only moderate, this is still often sufficient to produce significant results. This means that only some studies will not get published because they delivered "undesirable" results.
3. **Small studies** are at the greatest risk of generating non-significant findings, and thus of remaining in the "file drawer".




Cressey, 2017

# Small-Study Effect Methods

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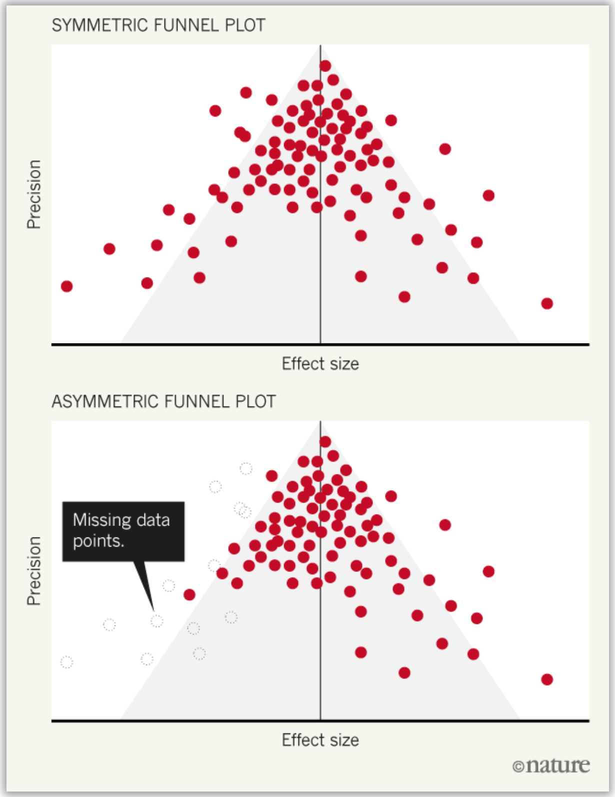
- In our meta-analysis, greater standard errors predict higher effect sizes

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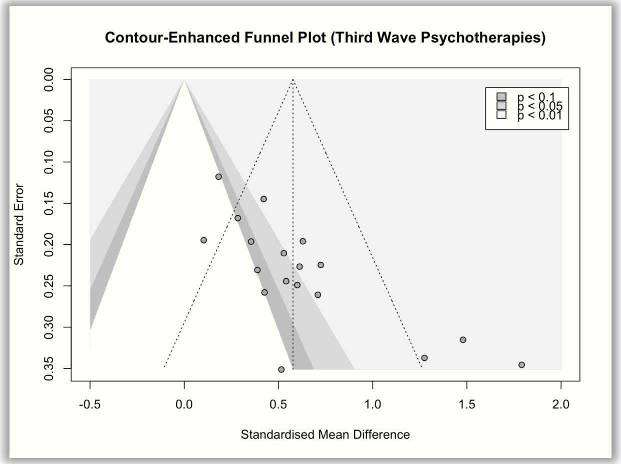
**Small-study effects result in funnel plot asymmetry**: instead of funneling out, the studies are “lopsided”, with smaller studies generating higher effects (on average).

- In our meta-analysis, greater standard errors predict higher effect sizes
- Asymmetry can be inspected visually, for example using **contour-enhanced funnel plots**



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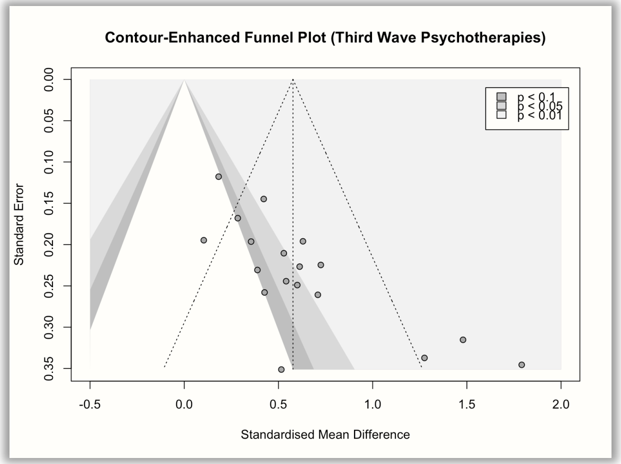
## Alternative explanations for funnel plot asymmetry

Although publication bias *can* lead to asymmetrical funnel plots, there are also "benign", causes that may produce similar patterns:

- **Between-study heterogeneity:** studies may be estimators of different true effects.
- **Study procedures** were different in small studies, and this resulted in higher effects.
- **Low-quality studies** tend to show larger effect sizes, because there is a higher risk of bias. Large studies require more investment, so it is likely that their methodology will also be more rigorous.
- Funnel plot asymmetry may simply occur by **chance**.



# Small-Study Effect Methods

## Egger's Regression Test (Egger et al., 1997)

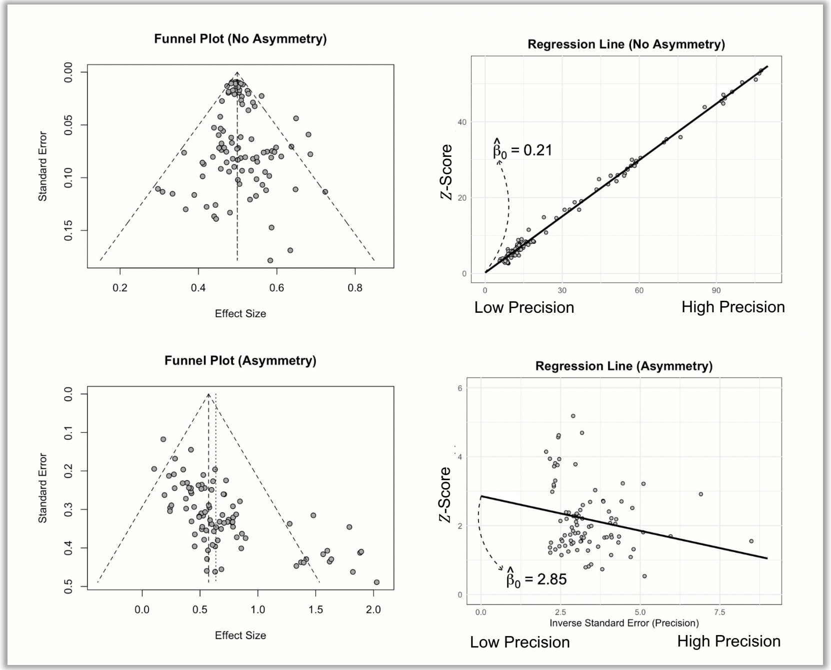
**Tests the association of standard error and effect size**

$$Z = \frac{\hat{\theta}_k}{\mathrm{SE}_{\hat{\theta}_k}} = \beta_0 + \beta_1 \mathrm{SE}_{\hat{\theta}_k}^{-1}$$

→ if $\hat{\beta}_0 > 0$ (based on a $t$-test) we conclude funnel plot asymmetry.

The test is therefore also known as **Egger's test of the intercept**.

This does not automatically mean that the results are burdened by publication bias!



# Small-Study Effect Methods

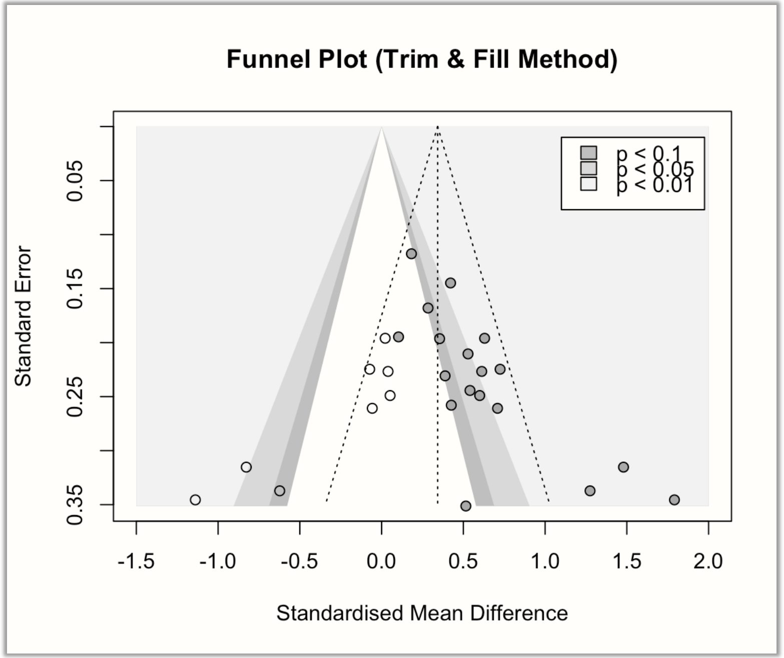
## The Trim and Fill Method (Duval & Tweedie, 2000)

**Adjusting the effect size for funnel plot asymmetry**

**Based on an algorithm:**

1. Identify all the **outlying studies in the funnel plot** (e.g., small studies scattered around the right side of the plot)
2. Once identified, studies are **trimmed**: they are removed from the analysis, and the pooled effect is recalculated without them.
3. **Filling:** the recalculated pooled effect is now assumed to be the center of all effect sizes. For each trimmed study, one additional effect size is added, mirroring its results on the other side of the funnel.
4. Based on all data, including the trimmed and imputed effect sizes, the average effect is **recalculated**

The result is then used as the estimate of the corrected pooled effect size.



# Small-Study Effect Methods

## Limit Meta-Analysis (Rücker et al., 2011)

**Adjusting the effect size for funnel plot asymmetry**

- Based on a model that allows the **standard error** of a study to **interact with its effect size** (as expected when there are SSE)
- Tries to "remove" the small sample effects by creating **"shrunken" estimates** that we would appear as the standard error goes to zero.
- This results in a heavier correction for small studies than for large studies, since the effect is stronger for studies with large standard errors
- Accounts for between-study heterogeneity during the computation
- Conceptually related to the idea of Egger's Regression Test
- Similar method (but without consideration of between-study heterogeneity): **PET-PEESE** (Stanley & Doucouliagos, 2014)