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Guillermo Montes
Children's Institute, Inc., GMONTES@CHILDRENSINSTITUTE.NET

Bohdan S. Lotyczewski
Children's Institute, Inc.

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Correcting Publication Bias In Meta-Analysis: A Truncation Approach

Guillermo Montes   Bohdan S. Lotyczewski
Children's Institute, Inc.

Meta-analyses are increasingly used to support national policy decision making. The practical implications of publications bias in meta-analysis are discussed. Standard approaches to correct for publication bias require knowledge of the selection mechanism that leads to publication. In this study, an alternative approach is proposed based on Cohen's corrections for a truncated normal. The approach makes less assumptions, is easy to implement, and performs well in simulations with small samples. The approach is illustrated with two published meta-analyses.

Key words: Meta-analysis, methods, truncation, publication bias

Introduction

> Publication bias presents possibly the greatest methodological threat to the validity of a meta-analysis. It can be caused by the biased and selective reporting of the results of a given study, or, more seriously, by the selective decision to publish the results of the study in the first place. Undetected publication bias is especially serious owing to the fact that the meta-analysis may not only lead to a spurious conclusion, but the aggregation of data may give the impression, with standard statistical methodology, that the conclusions are very precise. (Cooper & Hedges, 1994, p. 407).

With these words, Cooper and Hedges (1994) concluded their discussion on the detection and correction of publication bias in meta-analysis. For all its theoretical and practical importance, it is not often that one sees a meta-analysis corrected for publication bias.

Address correspondence to: Guillermo Montes, Children's Institute, Inc., 274 N. Goodman St., Suite D103, Rochester, NY, 14607. E-mail: gmontes@ childrensinstitute.net. Telephone: 585.295.1000 ext 227.

Undoubtedly, the reason is that the methodology available to the address the problem (Vevea & Hedges, 1995; Hedges & Vevea, 1996; Cleary & Casella, 1997) is complex, not easily accessible to the average meta-analyst practitioner and has been unable to make a strong practical case for supporting its use. The problem is difficult because publication bias, by its own nature, is a phenomena we know little about and because it does not suffice to show that, theoretically, a corrected estimate exists. One must show that the correction performs better than the original biased statistics in small samples.

In spite of these practical problems, the struggle against the effects of publication bias should not be abandoned. The presence of publication bias can lead to an erroneous consensus regarding the efficacy of a class of interventions or the importance of a particular factor in a psychological process of interest. Moreover, because one cannot assume that the same level of publication bias exists across meta-analyses, even in related content areas, there is little solid ground on which to base comparisons across meta-analyses.

Not only is the scientific community in danger of conceding to the evidence what the evidence does not warrant; but often social scientists are called to testify to critical allocations of funds and to the implementation of far-reaching social policies. Meta-analytic evidence plays an increasing role in those policy discussions as legislators and other policy makers demand simple summaries of complex information. Therefore, publication bias can also lead to harm in the public policy arena.

To be widely used, a method for correcting publication bias in meta-analysis must meet the following criteria: 1) It must recover the true population parameters in large samples, 2) it must be an improvement over the biased sample statistics in small samples, and 3) it must be relatively easy to calculate and easy to use for the average meta-analytic practitioner.

Modeling Publication Bias: Two Approaches

Traditional approaches to correct meta-analysis require some model for observed effect sizes that incorporates the selection process. Two aspects to such a model are given, the selection model and the effect size model. (Hedges & Vevea, 1996). Typically, the effect size model has been constructed using the random effects model and assuming a normal compound distribution. The selection process is modeled as a complex weight function of the probability of obtaining significant results based on sample size. This approach is based on the notion that publication bias is directly related to the presence of significant results.

This approach, commonplace in the literature, has a number of problems. First, it is unclear whether significance is the only criteria that impacts publication bias, effect sizes may be equally important, particularly when the sign is unexpected. Second, the selection process is an unknown and complex social phenomenon. Modeling publication bias as a function of a process we know little about seems unwise.

An alternative approach is to use a simple truncation model, based not on statistical significance but on effect size. After all if publication bias is having an impact on the overall results of a meta-analysis is because the bias is systematically truncating one of the tails, typically the left tail, of the distribution of program effects.

Because the standard approach assumes normality, modeling publication bias with a truncated normal model may be a practical alternative to modeling selection processes without imposing additional unverified assumptions; at least until the selection processes are better understood.

The truncation approach is more practical than the standard approach for three reasons. First, detecting publication bias becomes an exercise in elementary statistics. Is the observed distribution of effects normal or it is missing one of the tails? Both a standard histogram of the observed distribution and the computation of the distance between the median and the mean in standard deviation units can be used to answer this question.

Second, although we provided a rationale for our approach, the truncation model does not require us to specify a selection mechanism or to know how publication bias occurs. All we need to know is that there were no published studies below a particular effect size, and that the observed distribution of effects is skewed to the right. Truncation relies exclusively on the assumption of normality of the effect size model.

Third, it simplifies the correction for publication bias considerably because it uses a long-time developed method already in use in other disciplines as the standard way to deal with the statistics of truncated phenomena. Since 1959 engineers, economists, cosmologists and physicists have used Cohen's (1959) estimates for the population mean and standard deviation of a truncated normal to investigate truncated phenomena.

Cosmologists observe only the brightest stars, engineers observe only products that meet tolerance checks, economists observe only portions of the income distribution and particle physicists observe only the energy signature of higher energy particles. Similarly, highly effective programs are likely to be observed in the published literature while less effective interventions with non-significant or negatively significant results are likely to become unavailable results. Meta-analysis can benefit from the research and development of truncation-related statistics in other fields. These include truncation regression, correction for doubly truncated normals and many others (Greene, 1990).

Correcting for Publication Bias in Meta-Analysis

Assume that the distribution of effects is normal. One can model the distribution of effects in a variety of ways but the simplest method is to posit a compound normal where each study would be a realization of a normal distribution with mean Δ. Where Δ represents the true effect sizes of each actual intervention. Yet, each true intervention effect size Δ is itself a random variate of a normal distribution with mean μ. μ represents the true effect size of a class of interventions.

The resulting distribution of effects is a compound normal distribution:

$$N(\Delta,\sigma) \underset{\Delta}{\wedge} \quad N(\mu,\sigma').$$

It can be shown (Johnson, Koptz, & Balakrishnan, 1994) that such distribution is also normal with $N(\mu,\sqrt{\sigma^2+\sigma'^2})$.

Consider now the presence of publication bias. Because of the reasons described above, effect sizes below some level T are unlikely to be published. The resulting observable distribution of effect sizes will be a truncated normal.

Truncation of the left tail of a normal distribution produces the following effects: 1) the sample mean will overestimate the true mean, and 2) the sample standard deviation will underestimate the true standard deviation.

In other words, publication bias will result in the systematic overestimation of average effect sizes and the lowering of the associated standard deviation resulting in the illusion of precision that Cooper and Hedges (1994) described as one the greatest threats to the validity of meta-analysis.

Correction for truncation

Cohen (1959) first developed estimation procedures to recover the mean and standard deviation from a truncated observed normal distribution. Equations 1-5 describe the process. First, calculate the left-hand side of equation 5, using the minimum observed value in the truncated distribution as a proxy variable for T. Then solve for ξ and calculate θ(ξ). There are two ways of making the process less painful. One can look up the value of θ(ξ) in Cohen's book (1991, Table 2.1.) Alternatively, one can use a numerical solver, now standard in many applications, to numerically solve for ξ .

Once θ(ξ) is known, calculate μ_C and σ^2_C using equations 1 and 2. Note that the estimated degree of truncation is simply Φ(ξ).

$$\mu_R = \bar{x} - \theta(\xi)(\bar{x} - T) \quad (1)$$

$$\sigma_R^2 = s^2 + \theta(\xi)(\bar{x} - T)^2 \quad (2)$$

$$\xi = \frac{T - \mu_R}{\sigma_R} \quad (3)$$

$$\theta(\xi) = \frac{Q(\xi)}{Q(\xi) - \xi}$$

$$Q(\xi) = \frac{\phi(\xi)}{1 - \Phi(\xi)}$$

$$\frac{s^2}{(\bar{x} - T)^2} = \frac{1 - Q(\xi)(Q(\xi) - \xi)}{(Q(\xi) - \xi)^2}$$

Cohen's formulas to calculate the 95% confidence interval around the mean and standard deviation are:

$$\phi_{11} = 1 - Q(Q - \xi)$$

$$\phi_{12} = Q(1 - \xi(Q - \xi))$$

$$\phi_{22} = 2 + \xi\phi_{12}$$

$$\mu_{11} = \frac{\phi_{22}}{\phi_{11}\phi_{22} - \phi_{12}^2}$$

$$\mu_{22} = \frac{\phi_{11}}{\phi_{11}\phi_{22} - \phi_{12}^2}$$

$$V(\mu_R) = \frac{\sigma_R^2}{N}\mu_{11}$$

$$V(\sigma_R) = \frac{\sigma_R^2}{N}\mu_{22}$$

$$95\% CI\mu_R = (\mu_R - 2\sqrt{V(\mu_R)}, \mu_R + 2\sqrt{V(\mu_R)})$$

where Q is evaluated at ξ.

A Large-Sample Example

To illustrate the process, consider a class of interventions whose true effect size is 0.4 with a 0.8 standard deviation. Because of the large standard deviation, if 2000 studies were performed on this class of interventions one would expect that 20% of the studies would have negative results, some of them with considerable effect sizes (e.g., -0.8 and below).

Assume that there is no theoretical explanation for a negative effect size, so studies showing negative effect sizes are unlikely to be published. In the random sample we generated, that would leave 1393 publishable studies with some of them reporting non-significant results.

A meta-analysis performed on the 1393 studies would yield a biased sample mean of 0.82 with a biased standard deviation of 0.55. By all accounts, this class of interventions would be deemed to have large effects. Cohen's corrected estimates are 0.475 [95% CI (0.3723,0.5776)] for the mean and 0.77 [95% CI (0.709-0.829)] for the standard deviation. As can be seen, these estimates are quite close to the true values of 0.4 and 0.8.

As mentioned before, once the original mean and standard deviations have been recovered one can calculate the degree of truncation by simply calculating the value of the cumulative normal with the recovered mean and standard deviation at the truncation point, $\Phi(\xi)$. In this case, the degree of truncation was 26.84%.

Behavior of the Estimator in Small Samples

For Cohen's estimates to be useful in the correction of meta-analysis publication bias they need perform adequately in small samples. The standard criteria of using 95% confidence intervals does not seem appropriate in this small sample context. Some severely truncated samples will have sample sizes of below 15 observations and, therefore we expect that the 95% confidence interval of the corrected mean will contain the biased sample estimate. Other approaches to correct publication bias have the same problem (Vevea & Hedges, 1995). Therefore, we studied the direct improvement of using Cohen's formulas in terms of distance to the true parameters.

The population parameters were picked to represent meta-analytic results of importance both for scientific and policy purposes. We chose a large effect (0.8) with a relatively small standard deviation (0.4) and a total sample size of 100 published and unpublished studies (of which only a few will be published under high truncation).

Maxwell and Cole (1995) stated that "simulation studies are experiments and must be described and interpreted in this light". Therefore, we will use the language of experiments to describe our simulations. Table 1 shows the result of an experiment designed to answer seven questions and analyze how the answers vary as the truncation level increases:

- Question 1: What is the average sample bias for μ?
- Question 2: What is the average sample bias for σ?
- Question 3: What would be the average number of studies published?
- Question 4: What is the average error in correction for μ using Cohen's estimates?
- Question 5: What is the average error in correction for σ using Cohen's estimates?
- Question 6: On average, by how much do we benefit by performing the correction?
- Question 7: In what percentage of samples would the meta-analyst practitioner benefit from using Cohen's estimates?

To answer these questions we simulated 10,000 samples of a normal distribution of effect sizes mean = 0.8 and sd = 0.4. We then truncated it to create an observed distribution. We used the four different points of truncation ranging from almost no truncation (2 standard deviations below the mean) to severe truncation (one standard deviation above the mean). Then we used Cohen's (1959) formulas to estimate the corrected mean and standard deviation.

To answer questions 6 and 7 we defined an improvement measure as the ratio of two distances. The numerator is the distance between the sample moment from the biased distribution and the corresponding true value. The denominator is the distance between the corrected estimate and the true value. We used the absolute value measure of distance (although in the next section we also ran simulation with the Euclidean distance without substantial differences).

$$IMPROVE_{\mu} = \frac{Dist(\bar{x}, \mu)}{Dist(\mu_R, \mu)} = \frac{|\bar{x} - \mu|}{|\mu_R - \mu|}$$

for the mean; and

$$IMPROVE_{\sigma} = \frac{Dist(s, \sigma)}{Dist(\sigma_R, \sigma)} = \frac{|s - \sigma|}{|\sigma_R - \sigma|}$$

for the standard deviation.

An improvement factor below one indicates that the correction gets us farther way from the true value, an improvement factor of one indicates that the correction does as badly as the biased sample moments; finally, improvement factors higher than one indicate how much closer the correction for truncation gets us to the true mean (e.g. a value of 2 would indicate that Cohen's correction gets us two times closer to the real mean than the biased estimates do).

Since the improvement factors are always positive, their distribution is not likely to be symmetric; therefore, we report the median improvement, as the preferred measure of central tendency. This median will be the answer provided to question 6.

Because it is possible to have large average improvements while the majority of the samples would not be improved by using Cohen's corrections, question 7 asks the proportion of the 10,000 that benefit from the correction. Benefit is defined as having an improvement factor strictly higher than one. It is a measure of the risk that an average meta-analyst practitioner incurs by correcting the estimates of her study.

Table 1. Results of Experiment 1.

	Almost none	Mild	Serious	Severe
Truncation point (T)	μ-2 σ=0	μ-σ=0.4	μ=0.8	μ+σ=1.2
Truncation level Φ(T)	0.023	0.1586	0.5	0.841
Average Observed Sample Size	97.73	84.12	50.03	15.88
Average Sample Bias (for μ)	0.022	0.114	0.319	0.610
Average Sample Bias(for σ)	-0.024	-0.084	-0.161	-0.227
Average Error in Correction (for μ)	-0.017	-0.040	-0.150	0.116
Average Error in Correction (for σ)	0.0123	0.016	0.033	-0.056
Median Improvement factor (for μ)	1.1724	2.147	1.889	4.233
Median Improvement factor (for σ)	1.375	2.378	2.202	2.597
% of Samples that benefited (μ)	52.83%	75.84%	72.70%	100%
% of Samples that benefited (σ)	56.68%	80.90%	80.80%	96.4%
95% CI range	0.48	0.939	0.921	11.29
Does CI contain sample mean?	100%	100%	100%	100%
Does CI contain true mean?	96.43%	96.93%	92.08%	85.68%
Simulations based on 10,000 random samples from the normal (0.8, 0.4) for each truncation level.				

Answer to Question 1: The overestimation of μ increases with truncation level ranging from 0.02 to 0.609.

Answer to Question 2: The underestimation bias of the standard deviation increases as the truncation gets progressively worse, but it does so at a slower rate than the sample mean. It ranges from -0.02 to -0.22.

Answer to Question 3: The observed sample size varies form 97 (almost the 100 possible publications) to about 15 in the case of severe truncation. It is, of course, a linear function of the truncation level.

Answer to Question 4: The average errors made in correcting for μ ranged form 0.02 to 0.15 in absolute value, roughly increasing in a non-linear manner with the truncation level. At all levels of truncation, the average correction error was smaller than the corresponding average bias.

*A*nswer to Question 5: The average error made in correcting for σ ranged from 0.01 to 0.05, roughly increasing in a non-linear manner with the truncation level. Answer to question 5. At all levels of truncation, the average correction error was smaller than the corresponding average bias.

Answer to Question 6: The median improvement from using the correction ranges form 1.17 to 4.23. In other words, Cohen's estimation method got us anywhere from 1.17 to four times closer to the true mean. The improvement function is a nonlinear function of the truncation level, increasing with the truncation level at early stages of truncation, decreasing until past the 0.5 truncation level to quickly ascend again.

The median improvement for the standard deviation ranged from 1.27 to 2.59. Again, the function is nonlinear with truncation level, although less dramatically non-linear than the improvement for the mean was.

Answer to Question 7: Regardless of the level of truncation, the correction for both μ and σ was beneficial in more than half of the cases. With mild truncation the proportion of samples that benefited from the correction were over 75%, there was a small decrease in the proportion of samples that benefit as truncation nears the 0.5 point and then a dramatic increase so that for serious truncation virtually all samples benefited form Cohen's correction. This nonlinear risk function was carefully investigated in the next section.

When almost no truncation is present (truncation level of 0.02) slightly half of the samples did not benefit from Cohen's correction. At that small level of truncation, however, both the error of the correction and the bias are unlikely to have substantial scientific or policy implications. As truncation increases, both the chances of benefiting from using Cohen's correction and the improvement in terms of distance to the true parameters are sizeable. Therefore, if truncation is detected, the use of Cohen's estimates seems warranted even for small sample sizes.

We now turn our attention to investigating in detail how the proportion of samples that benefit from correction increase as a nonlinear function of truncation level.

Proportion of Samples that Benefit from Cohen's Correction as a Function of Truncation

The experiment of the previous section yielded that the proportion of samples that benefit from Cohen's corrections were nonlinear functions of the truncation level $\Phi(\xi)$. To investigate these nonlinear functions further we generated 1000 random samples (μ=0.8, σ=0.4, N=100) for each of 121 levels of truncation ranging from $T=\mu-2\sigma=0$ to $T==\mu+\sigma=1.2$ at 0.01 intervals. We then plotted the percentage of samples that benefit from Cohen's correction for μ as a function of the truncation level, and proceeded similarly for σ. We repeated the process for different values of μ and σ but the nonlinear pattern remained essentially unchanged.

We employed the absolute value distance function in our improvement measure as before; but also generated a complete independent set of random samples and calculated the improvement factors using standard Euclidean distance function. Figure 1 and 2 show the results.

Figure 1. Samples Improved By Correction: The Mean

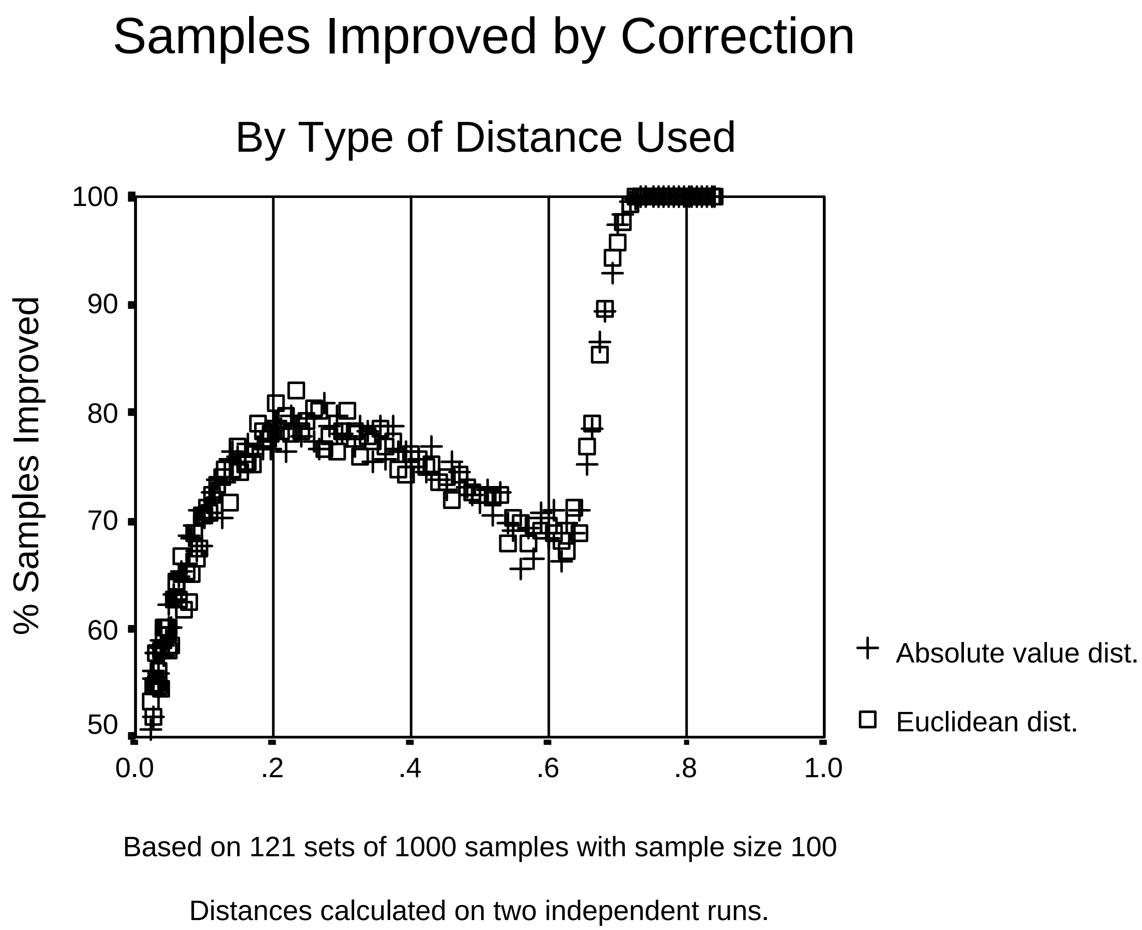
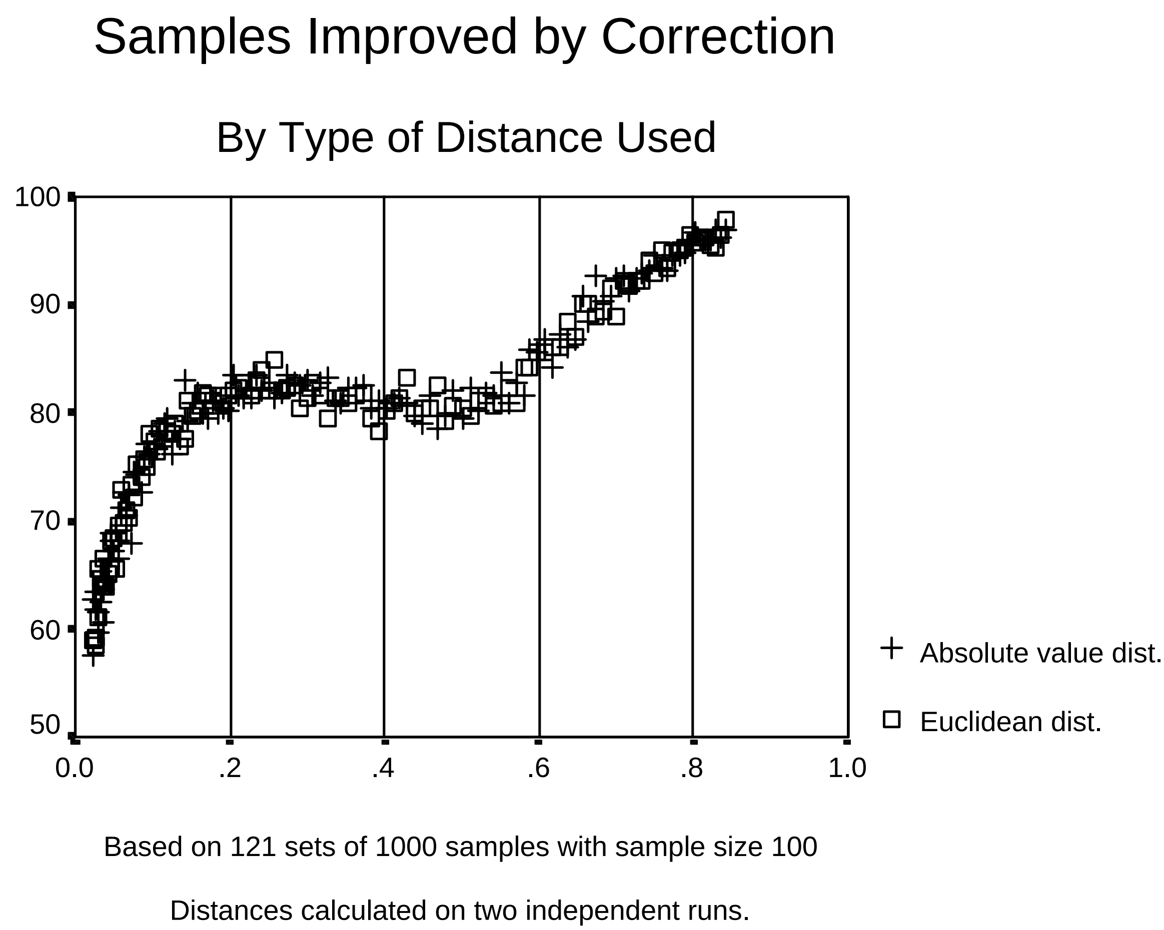


Figure 2: Samples Improved By Correction: The Standard Deviation.



Note the following patterns: 1) for all truncation levels, the proportion of samples that benefit from Cohen's correction for both μ and σ was over 50%, 2) for mild truncation levels, the proportion of samples that benefit from Cohen's correction increases quite rapidly until about $\Phi(\xi)=0.25$, 3) in the case of μ, the proportion of samples decreases until $\Phi(\xi)=0.65$ truncation level to then rise dramatically to 100%, and 4) in the case of σ, the proportion of samples stabilizes at about 80% until past the $\Phi(\xi)=0.5$ truncation level to then rise dramatically to almost 100%.

Therefore, Cohen's estimates perform adequately in small samples, with over 60% chance of obtaining a better point estimate through Cohen's estimation method. The correction seems to be particularly beneficial for the mild levels ($\Phi(\xi) \approx 0.2$) of truncation commonly believed to be present in meta-analysis.

Illustrative Examples

To demonstrate the applicability of the method we have chosen two meta-analysis. The meta-analysis were previously published by *Psychological Bulletin* and contained the necessary data to make the corrections. We are not presenting the corrections as substantive revisions, but simply as illustrations of the method. The two meta-analyses show different levels of truncation.

Example 1: Mild Truncation

The first example is taken from table 3 of Yirmiya, et al. (1998) meta-analysis comparing theory of mind abilities of individuals with autism, individuals with mental retardation and normally developing individuals. The data used here refers only to the comparison of individuals with autism versus normally developing individuals. The authors report different average statistics because they calculated a weighted average. We had no information to replicate the weights (sample size of the studies).

There were 22 effect sizes, with sample mean 1.1173, standard deviation 0.9667, median 1.030 and minimum value -0.40. The authors report different numbers because they used a weighted function to calculate average effect sizes.

The histogram of the observed distribution and the fact that the median was larger than the sample mean revealed mild truncation on the left size. Cohen's corrections are as follows: Corrected μ = 0.689, corrected σ =1.258. Degree of truncation 0.1933. Therefore, in this case the correction would cast some doubt on the average large effect differential between normally developing individuals and those with autism.

Example 2: No Truncation

The second example is taken from Appendix A of Rind, Tromovitch, and Bauserman's (1998) controversial meta-analysis on the assumed consequences of child sexual abuse using college samples. This is an example of real-world research in which it was easier to explain the lack of significant positive findings by using a number of methodological and theoretical arguments. Because of this, one would expect less truncation to have occurred.

Using the 56 studies, the average effect size is 0.0953, with a standard deviation of 0.0947 and a minimum observation of -0.25. The histogram revealed little or no truncation, as did the fact that the median was almost identical to the sample mean. The corrected mean was 0.09531. The point estimate is essentially identical to the uncorrected mean. The corrected standard deviation is 0.0948. The estimated degree of truncation was only 0.0001.

This example illustrates how some meta-analysis may suffer very little from publication bias because negative and positive results are interpretable in the context of new theories or methodological issues. It is also suggestive that at least part of the controversy regarding diverse meta-analytic findings from several types of studies may be due to the degree of publication bias.

Conclusion

Publication bias is an important threat to the validity of meta-analysis. It can lead to error regarding the efficacy of classes of interventions or the importance of particular factors in psychological processes. These errors can have a detrimental effect on both scientific knowledge and on public policy. Therefore, it is important to find some correction, even if imperfect, to the problem.

First, modeling publication bias by estimating a selection function of what remains a fundamentally unknown process seems to us unwise. Selection rules are likely to vary depending on the nature of the study, the availability of theoretical and methodological explanations for the unexpected result, the other results in the study, a very complex web of reputation and financial incentives, and the larger context of scientific or popular debate on the content of the study. Therefore, to correct publication bias using a selection approach one either needs to know the complexity of how the publication bias originated or oversimplify the problem substantially by using a simple mechanical rule. In either case, one is likely to impose additional assumptions on the data.

We make a case for using truncation instead of selection as a method to correct for publication bias on practical grounds: truncation does not require any additional assumptions beyond the normality of the effect size distribution; in particular it does not require us to know how the publication selection took place. Truncation is easy to detect in practice by looking at simple statistics like the difference between the median and the mean or plotting a histogram. It can be corrected by well-developed estimators currently in use by other disciplines with the attendant benefits of on-going research and development in the area.

In addition, our simulations demonstrate that in the small samples typical of meta-analytic studies Cohen's correction performs adequately. In cases of mild truncation (defined as around 20%), the proposed correction will, on average, get point estimates that are two times closer to the true parameters, and the correction will benefit over 70% of the samples. Therefore, the odds favor making the correction. The size of the correction is likely to have a substantial impact on the interpretation of the results.

Certainly, this approach is not perfect. The truncation approach is presented simply as an approximation to the real underlying structure of publication bias. Yet, complicating the statistics in favor of a more accurate portrayal of the underlying structure, given our wide ignorance of the phenomena and the increasing complexity of the statistics, seems to us not be a practical approach to a problem that has important policy ramifications. Given the seriousness of the potential damage publication bias may be doing both to social science and to public policy finding some correction procedure that requires minimal assumption and is easy to use seems to us as a more responsible course of action than ignoring the problem until a complete solution has been found.

References

Cleary, R. J., & Casella, G. (1997). An Application of Gibbs Sampling to Estimation in Meta-Analysis: Accounting for Publication Bias. *Journal of Educational and Behavioral Statistics*, *22*, 2, 141-154.

Cohen, A. C. (1991). *Truncated and Censored Samples: Theory and Applications*. New York, NY: Marcel Dekker Inc.

Cohen, A. C. (1959). Simplified Estimators for the Normal Distribution When Samples are Singly Censored or Truncated. *Technometrics*, *1*, 3, 217-237.

Cooper, H., & Hedges, L. V. (Eds) (1994). *The handbook of research synthesis*. New York: Russell Sage Foundation.

Greene, W. H . (1990). *Econometric Analysis*. New York: MacMillan Publishing Company.

Hedges, L. V., & Vevea, J. (1996). Estimating Effect Size Under Publication Bias: Small Sample Properties and Robustness of a Random Effects Selection Model. *Journal of Educational and Behavioral Statistics*, *21*, 4, 299-332.

Johnson, N. L., Kotz, S., & Balakrishnan, N. (1994). *Continuos Univariate Distributions.* V. 1. 2nd edition. NY: John Wiley & sons, Inc.

Maxwell, S. E., & Cole, D. A. (1995). Tips for Writing (and Reading) Methodological Articles. *Psychological Bulletin*, *118*, 2,193-198.

McEachern, W. A. (1994). *Economics: A Contemporary Introduction*. Cincinnati, OH: South-Western Publishing Company.

Rind, B., Tromovitch, P., Bauserman, R. (1998). A meta-analytic examination of assumed properties of child sexual abuse using college samples. *Psychological Bulletin*, *124*, 22-53.

Vevea, J. L., & Hedges, V. (1995). A General Linear Model for Estimating Effect Size in the Presence of Publication Bias. *Psychometrika*, *60*, 3, 419-435.

Yirmiya, N., Osnat, E., Shaked, M., & Solomonica-Levi, D. (1998). Meta-Analyses Comparing Theory of Mind Abilities of Individuals With Autism, Individuals With Mental Retardation, and Normally Developing Individuals. *Psychological Bulletin*, *124*, 3, 283-307.