Comments on Paldam, "Meta-Analysis in a Nutshell"

by Jon P. Nelson[1]

Martin Paldam's paper introduces techniques of meta-regression analysis, but it is heavily focused on one issue – publication selection bias. This is the current "hot topic," with new techniques and results appearing at a rapid pace in economics and other areas (e.g., Simonsohn et al. 2014). The beginning researcher who hopes to get something published that attracts attention from experienced analysts is wise to pay attention to Paldam's summary guidance. However, depending on objectives of the analysis, there are other issues that deserve attention. Much of what follows draws on my meta-review paper with Peter Kennedy (Nelson and Kennedy 2010) and Nelson (2015). Many of the ideas and guidance were laid out by early researchers, such as Gary Saxonhouse (1976), Kerry Smith (Smith and Kaoru 1990), Tom Stanley (Stanley and Jarrell 1989), and others.

1. Why Do Meta-Analysis?

There are three main reasons why economic researchers conduct meta-analyses, all of which are related to advantages of quantitative literature reviews. First, the analysis may be designed to inform public policy, especially policies that require a summary measure of effect size. Nelson and Kennedy (2010) review 140 meta-analyses from 125 studies in environmental and resource economics, and many of these have a strong public policy emphasis. For example, meta-analysis produces a weighted average effect size – say $\bar{\beta}$ – that is input for a benefit-transfer for water pollution abatement. In this context, Paldam's statement is important − meta-analysis requires that "the studies covered are so similar that their differences can be coded." It makes little sense to pool together highly diverse empirical studies – apples and oranges − that report on fundamentally different effect sizes (Smith and Pattanayak 2002; Van Houtven 2008). Second, the analysis may be designed to inform applied economists about expected results from different data sources, model specifications, and econometric methods. Lacking theoretical guidance, meta-regressions sometimes include dozens of covariates, mostly categorical dummy variables. I don't think this is useful for public policy objectives, where relatively simple averages and

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regression models might suffice. There are three common problems in meta-regressions: the null case is not clear or poorly constructed, making "meta-averages" difficult to interpret or construct; cell sizes are small, such that reported statistical tests are questionable; and data drawn from primary studies involve enough uncertainty that category dummies are certain to contain measurement error (see Aigner 1973). Analytical studies with the second objective also are more interesting when there is a hypothesis being tested and empirical evidence is mixed (e.g., effects of minimum wages). Third, the objective of a meta-analysis may be to advance the frontiers of economic science, which is the focus of Paldam's article and his other recent contributions. This is important, but my point is that a researcher's objective may stop well short of this frontier.

2. Weighted-Means First, Then Meta-Regressions

Meta-analysis was initially developed around the idea of weighted means, with two alternative sets of weights for each effect size in the sample. Using inverse variances as weights yields the "fixed-effect size" (FES) estimator, which assumes there is a common, or fixed, population effect size. Effect sizes are thus draws from a common, but unknown, distribution. Alternatively, if there is heterogeneity in the true effects, either *a priori* or based on a statistical test, then a "random-effects size" (RES) estimator is appropriate. RES weighted-means use an estimate of the between-study variance, which is added to the estimated variance of each effect-size. The inverse of this combined variance is used as a weight, and so RES gives greater weight to less precise estimates compared to FES models. RES also is the simplest method for incorporating study heterogeneity. In my experience, the RES mean is usually close the unweighted median.

Economists jump too quickly to meta-regressions. A better approach is to spend some time first digesting the data, even if the analytics are basically descriptive. After all, meta-analysis is just a form of literature review, and most reviewers would not think of reviewing only the conclusion of articles or skipping a description of the data in their own primary study. Most analysts use all estimates reported in each primary study, which violates the assumption of independent observations. In this context, Paldam discusses the importance of clustered standard errors as a method for dealing with multiple estimates. This is now a common solution, but it does not entirely resolve the issue of multiple estimates. Suppose researcher A publishes a paper – perhaps a book chapter – that contains 20 estimates. Researcher B is subject to limits on publication length, and publishes only 5 estimates for the same effect size. There is no sensible reason *a priori* for assigning the first study more weight than the second study, but that is exactly what happens in many meta-analyses in economics. There are several possible solutions to this problem, with starting points found in Hedges et al. (2010) and Nelson and Kennedy (2010).

3. Outlier Problems in Meta-Analysis

Paldam provides an insightful discussion of dispersion of estimates as affected by publication selection bias. The basic idea is that publication bias can be observed graphically in the funnel plot and then corrected using techniques of meta-regression analysis. However, there is another distributional issue involving outliers in effect sizes or outliers in standard errors. It seems likely this issue complicates tests for publication bias. Most empirical researchers have encountered outliers in their data, but in this case it is outliers in the sample of effect sizes or estimated standard errors. Recall that in a meta-analysis, observations are weighted by inverse variances, so more precise estimates receive greater weight. Provided estimates have desirable statistical properties (asymptotically unbiased, efficient, etc.), there is nothing fundamentally wrong here. However, most empirical researchers have encountered regression results with too large (or small) parameters or too small (or large) standard errors. Perhaps these results are due to particular combinations of collinear data, particular model specifications or estimation methods, or just the vicissitudes of empirical research.

When I first started doing meta-analysis, I used Excel and did weight calculations "by hand," so it was easy to observe the effects of "small" standard errors. As an example, suppose there are four significantly positive estimates for an income elasticity, with the following values and standard errors: 0.8 (0.4); 0.5 (0.2); 0.4 (0.2); and 0.1 (0.025). The unweighted mean and median are both 0.450. The FES mean is only 0.113 (0.025), with the following weights: 6.25, 25, 25, and 1600, respectively. The RES mean is 0.343 (0.151). Does it really make sense that the fourth estimate receives 64-times more weight than other significant estimates? It all depends on the properties of the reported estimates, but these are not under direct control of the meta-analyst. It might be possible to control indirectly for influential observations using covariates for data, model, method, time period, and so forth, but it is easy to overlook the problem and attach too much importance to precision. My recent papers use trimmed samples to address this issue (Nelson 2013, 2014). Similar issues arise in estimating weighted-least squares meta-regressions. Standard statistics for detecting outliers are probably not much help, but various robust regressions can help identify outliers, such as the MS-estimator (Bramati and Croux 2009; Maronna and Yohai 2000; Verardi and Croux 2009). Other useful software for observing weights is Comprehensive Meta-Analysis 3.0 (Biostat 2015) and an accompanying book with a medical emphasis by Borenstein et al. (2009).

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