Measurement Error Meta-Analysis

Measurement error is well known to create bias in parameter estimates and standard errors in path analysis models (Cole & Preacher, 2014). Nevertheless, path analysis is a commonly applied technique in psychological research. While cautions over the potential perils of the use of fallible measures have long been part of the methodological literature (Cole & Preacher, 2014; Kenny, 1979; Wansbeek & Meijer, 2000), to date no effort has been made to assess the actual impact of measurement error on reported path analytic results. Therefore, we reviewed all publications within six psychology journals between 2015 and 2017 and compared published results to replication results in which the replication employed a correction for measurement error using single indicator latent variables (SILV; Hayduk, 1987).

We reviewed all articles from six psychology and educational psychology between 2015 and 2017, and identified approximately 100 articles which were reanalyzable. To support reanalysis using SILV, several pieces of information are required: a correlation or covariance matrix, estimates of reliability for study variables, and a precise description of the model employed. We only considered models with at least one mediating path, as more complex models are expected to suffer the effects of measurement error more severely (Cole & Preacher, 2014). When an individual paper reported on multiple path analyses for a single sample, only the most complex path analysis was considered herein.

Replicable models were reanalyzed using provided summary data. Model replication was considered successful if each path was estimated with an absolute bias of less than 0.1 between the reported and replicated models. Models that were accurately replicated were then reanalyzed using the SILV correction technique. The bias between standardized path coefficients from the replication and corrected replication models represents the expected amount of bias due to measurement error. Absolute bias was chosen for analysis rather than relative bias due to the possibility of extreme relative bias with small path coefficients.

To date, 17 of the identified models have been successfully reanalyzed. Of these, seven exhibited at least one standardized path with an expected bias of at least 0.1, with the largest bias being 0.167. For each reanalyzed model, the average expected bias and largest expected bias amongst paths were regressed on the number of variables, the number of direct paths, and the minimum reliability of variables in the model. Minimum reliability was the only significant predictor, explaining over 45% of variance in average bias and over 50% of the variance in largest bias. Of note is that none of the five models with minimum reliability above .80 had a largest bias greater than 0.1.

In published path analyses re-analyzed thus far, the degree of expected bias in path coefficients has been fairly minimal, particularly when all reliability estimates are above the commonly recommended level of .80 (e.g., Nunally, 1978; Raykov & Marcoulides, 2011). Should this trend be generally applicable, the dire warnings of Cole and Preacher (2014) would amount to a tempest in a teapot.

References

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