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Robustness of statistical inferences using linear models with meta-analytic correlation matrices

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ABSTRACT

To examine complex relationships among variables, researchers in human resource management, industrial-organizational psychology, organizational behavior, and related fields have increasingly used meta-analytic procedures to aggregate effect sizes across primary studies to form meta-analytic correlation matrices, which are then subjected to further analyses using linear models (e.g., multiple linear regression). Because missing effect sizes (i.e., correlation coefficients) and different sample sizes across primary studies can occur when constructing meta-analytic correlation matrices, the present study examined the effects of missingness under realistic conditions and various methods for estimating sample size (e.g., minimum sample size, arithmetic mean, harmonic mean, and geometric mean) on the estimated squared multiple correlation coefficient (R^2) and the power of the significance test on the overall R^2 in linear regression. Simulation results suggest that missing data had a more detrimental effect as the number of primary studies decreased and the number of predictor variables increased. It appears that using second-order sample sizes of at least 10 (i.e., independent effect sizes) can improve both statistical power and estimation of the overall R^2 considerably. Results also suggest that although the minimum sample size should not be used to estimate sample size, the other sample size estimates appear to perform similarly.

1. Introduction

As empirical studies accumulate within a domain (e.g., human resource management, industrial-organizational psychology, and organizational behavior), researchers use meta-analysis to statistically combine results to derive stronger conclusions than those afforded by any single study (Hunter & Schmidt, 2004). By pooling data across individual, or primary, studies, one can reduce the influence of sampling error to produce point-estimates of statistical effects, or at least to identify typical trends for a set of ambiguous or conflicting findings. Additionally, meta-analysis enables researchers to examine potential moderators of those effects (Cortina, 2003; Hedges & Olkin, 1985; Hunter & Schmidt, 2004), even if no primary study examined them (i.e., moderators representing differences between study designs or samples across studies). Yet, researchers may also experience frustration due to the rather limited set of conclusions produced by the meta-analytic method. A single meta-analysis cumulates information for just one effect size, which typically represents the relation between only two variables (e.g., correlation coefficient, odds-ratio, or Cohen's *d* indexing the difference between experimental conditions). Examinations of multiple relations within a complex network can only be performed in a subjective, piecemeal fashion with meta-analytic results.

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Fortunately, advances in quantitative theory and computing technology have facilitated the development of more sophisticated approaches for interpreting meta-analytic data. Specifically, the scientific literature reveals that there is an increasing trend for researchers in human resource management, industrial-organizational psychology, organizational behavior, and related fields to use linear models (e.g., multiple linear regression) with meta-analytically derived results as raw data (Cheung & Chan, 2005). These methodological approaches hold much appeal because they enable theory building and tests of complex models (Furlow & Beretvas, 2005; Viswesvaran & Ones, 1995).

In human resource management and allied fields, numerous studies have applied linear models to meta-analytic data. For example, Christian, Garza, and Slaughter (2011) examined whether engagement partially mediated the relation between job characteristics and job performance. In addition, Gajendran and Harrison (2007) investigated whether the relation between telecommuting and performance is mediated by autonomy. As another example, Riketta (2008) posited that job attitudes (e.g., commitment and satisfaction) influence job performance but not the other way around. Eatough, Chang, Miloslavic, and Johnson (2011) examined the mediating effect of job satisfaction on the relation between role stressors and organizational citizenship behavior. Zhao, Wayne, Glibkowski, and Bravo (2007) tested whether affect mediated the relation between psychological contract breach and individual effectiveness.

Notably, when meta-analyses are designed to estimate correlations for a network of variables, primary studies typically contribute effect size data for just a portion of those variables; estimates for some bivariate relations are missing values within the meta-analytic dataset established for testing hypotheses. These missing data may then bias results for tests of linear models applied to meta-analytic data structures, such as correlation matrices (Burke & Landis, 2003). Furthermore, when conducting statistical tests for such linear models, missing data prevent accurate calculations of standard errors. In a meta-analytic correlation matrix, for example, cells may be based on a different number of effect sizes provided by different subsets of primary studies. Thus, each cell is associated with a different aggregated sample size (Burke & Landis, 2003; Schafer & Graham, 2002; Viswesvaran & Ones, 1995), such that the sample size for the entire matrix is undetermined. Researchers have proposed different ways to *estimate* the sample size of a meta-analytic correlation matrix, but the extent to which an estimate is too inappropriately large or small can affect Type I error rates (Furlow & Beretvas, 2005) or statistical power (Cheung & Chan, 2005; Roth, Switzer, & Switzer, 1999).

In this study, we examined how multiple regression results based on meta-analytically derived data are affected by missing data. Although researchers have used a variety of methods (e.g., arithmetic mean or harmonic mean) to estimate the sample size of a meta-analytic correlation matrix, no method has been supported empirically as more effective than another. Thus, this study also focused on comparing the effectiveness of such sample size estimates under realistic conditions of missing meta-analytic data.

1.1. Missing data in meta-analysis

Ideally, meta-analyses would aggregate the same type of data across all studies, when the focus is on estimating relations between specific variables within a network. Each primary study would contribute effect size data for every relation between the variables examined. The resultant data structure would then contain effect sizes all derived from the same set of primary studies, and the aggregated sample size for the matrix would simply be $N =$ sum of cases (n) across all primary studies (k). In reality, most meta-analytic databases are constructed in a piecemeal fashion, with each primary study contributing a varying number of effect sizes to each meta-analytic calculation.[1] Thus, the aggregated data produce structures (e.g., correlation matrix) with substantial amounts of missing data; each effect size is based on a different aggregated sample size (N). Additionally, data may be missing within each primary study at the level of individuals. Thus, missing data can occur at multiple levels in meta-analysis (Furlow & Beretvas, 2005): by individuals within a primary study and by primary studies within a meta-analysis.

Based on theory (Rubin, 1976; Schafer & Graham, 2002), three general reasons explain why data may be missing at any level: missing completely at random (MCAR), missing at random (MAR), or missing not-at-random (MNAR). Although MCAR occurs often enough in research, it generally poses the fewest problems because it leaves statistical estimates unbiased. On the other end of the continuum, MNAR poses the most serious threat to statistical inferences because data are missing for a substantive reason (e.g., participants chose to withhold responses, experimenter error in coding or entering data, etc.). MNAR represents situations when the likelihood that a value is missing depends on the true value itself, meaning that missingness is explained by a factor unrelated to the observed variables in the data set (Paul, Mason, McCaffrey, & Fox, 2008; Schafer & Graham, 2002). MAR reflects intermediate situations where the likelihood that a value is missing depends on observed data that were collected, but not other variables. Because multiple imputation techniques predict missing values based on observed values, they can address MAR situations reasonably well. In practice, however, missing data can result from any combination of these three causes (Graham, 2009; Roth et al., 1999).

Despite MNAR posing the most realistic and puzzling challenges for analysts, researchers tended to avoid modeling MNAR situations due to the added complexity (Cheung & Chan, 2005; Pastor, 2003) until fairly recently (e.g., Furlow & Beretvas, 2005). Also, research has typically modeled missing data abstractly, without linking procedures to realistic, substantive causes of missing data in practice (e.g., Allison, 2003; Graham, 2009).

Although general discussions of missing data have tended to ignore meta-analytic contexts entirely (e.g., Graham, 2009), it is important to develop some understanding of the reasons why primary studies have missing data (i.e., effect sizes), as those may be distinct from reasons for missing responses by individuals within a primary study. Perhaps researchers decided against reporting non-

[1] Although meta-analysts might be absolved of "creating" a missing data problem because they had no part in designing the primary studies, they are responsible for establishing inclusion processes and criteria that produce complete meta-analytic datasets. As existing theories of missing data already account for situations in which "missingness" results from both design flaws and unanticipated, uncontrollable factors, they provide useful frameworks for understanding how to manage similar scenarios in meta-analysis.