Computer Program Exchange

Computation of Effect Size for Moderating Effects of Categorical Variables in Multiple Regression

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The computation and reporting of effect size estimates is becoming the norm in many journals in psychology and related disciplines (Kendall, 1997; Thompson, 1994; Zedeck, 2002). Despite the increased importance of effect sizes, researchers may not report them or may report inaccurate values because of a lack of appropriate computational tools. For instance, Pierce, Block, and Aguinis (2004) provided examples of articles published in prestigious journals such as *Psychological Science, Developmental Psychology*, *Journal of Educational Psychology*, and *Journal of Abnormal Psychology*, in which researchers erroneously reported partial eta-squared values as representing classical eta-squared values. One likely reason for why researchers do not report effect size estimates or, even worse, report inaccurate values is that most commercially available statistical software packages provide only a limited number of effect-size estimates (e.g., η^2 but not f^2).

The use of multiple regression to estimate moderating (i.e., interaction) effects of categorical variables involves an ordinary least squares (OLS) regression equation that examines the relationship between a predictor X and categorical moderator Z with a criterion Y. The OLS model, labeled moderated multiple regression (MMR), includes the first-order effects of X and Z and the product term between X and Z that represents their interaction (Aguinis, 2004; Cohen, Cohen, West, & Aiken, 2003). The use of MMR is pervasive in psychology, management, and related disciplines. For example, researchers have used MMR to test hypotheses in domains such as job performance, stress, and preemployment testing (for additional examples, see Aguinis, 2004; Aguinis, Boik, & Pierce, 2001; Aguinis & Stone-Romero, 1997).

The effect-size metric f^2 is used in MMR to describe the strength of a moderating effect (Aiken & West, 1991). Specifically, f^2 is the ratio of systematic variance accounted for by the moderator variable relative to unexplained variance in the criterion. In MMR, homogeneity of error variance is a key statistical assumption that, when violated, biases results of the analyses (Aguinis & Pierce, 1998). Homogeneity of error variance exists when the variance in Y that remains after predicting Y from X is equal across moderator-based subgroups (Gulliksen & Wilks, 1950). Unfortunately, unbeknownst to researchers, the homogeneity of error variance assumption is violated frequently (Aguinis, Petersen, &

Applied Psychological Measurement, Vol. 30 No. 5, September 2006, 440–442

DOI: 10.1177/0146621606286314

Pierce, 1999), which often makes the computation of f^2 using the traditional equation inappropriate (Aguinis, Beaty, Boik, & Pierce, 2005). Accordingly, Aguinis et al. (2005, Appendix A) derived and provided proof for the appropriateness of a modified version of the f^2 effect-size estimate that is suitable for situations involving heterogeneity of error variance in MMR.

The computations involved in calculating Aguinis et al.'s (2005) modified f^2 statistic are quite complex. Accordingly, to make the computation of Aguinis et al.'s modified f^2 more accessible and to increase the likelihood of its accuracy, we developed a computer program in August 2005 that can be executed online or downloaded and executed locally. The program was written in Java so that it can be executed on any computer regardless of platform and operating system. The program is available free of charge at the following URL: http://carbon.cudenver.edu/~haguinis/mmr/fsquared. The program allows for analyses with moderators that have 10 or fewer categories (i.e., $k \leq 10$). Users must first specify the number of categories (i.e., moderator-based subgroups) involved in their analysis. To estimate the effect size, population parameters shown in the Aguinis et al. equations can be substituted with sample statistics. Also, computations can be conducted using moderator-based subgroup correlation coefficients or regression coefficients; thus, users must first specify whether correlations or regression weights will be used as input. In addition, for each moderator-based subgroup, the program requires the user to input the following information: (a) standard deviation for the criterion Y, (b) sample size, and (c) standard deviation for the predictor X. After inputting these data, users click the "Calculate" icon, and the program reports a modified f^2 value. As an example, if an obtained f^2 value is .037, the interpretation is that the moderator variable explains 3.7% of the criterion variance that was unexplained by the first-order and second-order (i.e., interactive) effects of all predictors in the MMR equation.

As an index of relative importance, the obtained f^2 value can be compared to Aguinis et al.'s (2005) findings. Aguinis et al. reviewed all studies that used MMR to estimate moderating effects of categorical variables that were published between 1969 and 1998 in three of the most prestigious applied psychology and management journals. Aguinis et al. computed modified f^2 values for each of these studies. Based on 261 effect-size estimates, the mean f^2 was .009, the 25th percentile was .0004, the 50th percentile was .002, and the 75th percentile was .0053. Thus, our illustrative effect-size estimate of .037 is more than four times larger than the mean effect size estimate reported by Aguinis et al. This information alone is not sufficient to conclude that the effect size is practically significant. Before drawing this conclusion, information is required regarding the specific research context and expected outcomes. Nevertheless, knowing that one's effect size is more than four times larger than the average effect size reported in 30 years of research published in *Journal of Applied Psychology, Personnel Psychology*, and *Academy of Management Journal* is an indicator that the effect size should probably not be taken lightly.

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