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Correcting for Measurement Error in Detecting Unconscious Cognition: Comment on Draine and Greenwald (1998)

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A. G. Greenwald, M. R. Klinger, and E. S. Schuh (1995) have proposed a regression method for detecting unconscious cognition in experiments that obtain measures of indirect and direct effects of stimuli with suspected unconscious effects. Their indirect-on-direct-measure regression approach can produce misleading evidence for indirect effects in the absence of direct effects when the direct-effect measure has typical measurement error. This article describes an errors-in-variables variant of the regression method that corrects for error in the direct-effect measure. Applied to the uses of the regression method by S. C. Draine and A. G. Greenwald (1998) in this issue, the errors-in-variables method affirms substantial evidence for indirect effects in the absence of direct effects.

The interpretation of a given set of data as demonstrating unconscious processing of stimuli encounters several difficulties. In studies of unconscious cognition, researchers often attempt to show indirect without direct effects of stimuli. A direct effect of a stimulus is its effect on a response according to explicit instructions. An indirect effect is an uninstructed effect of the stimulus on task behavior. To demonstrate the absence of direct effects, it is necessary to accept the null hypothesis that the stimulus had no influence on the measure of direct effects, which is problematic statistically (Reingold & Merikle, 1988). Additional difficulties have been discussed by Greenwald, Klinger, and Schuh (1995) and Reingold and Merikle (1988), among others.

Greenwald et al. (1995) have proposed a new method to overcome some of these problems in demonstrating unconscious processing. The method is based on a regression analysis in which an indirect measure is regressed on a comparable direct measure. In the regression analyses by Greenwald et al. (1995), the dependent variable and the predictor variable are the measures of indirect and direct effects, respectively. The finding of greatest interest is that of an intercept significantly larger than zero because it implies indirect without direct effects. Because demonstration of a positive intercept requires rejecting rather than accepting a null hypothesis, the previously mentioned statistical problem is overcome in this approach.

There is however a new statistical problem (Greenwald & Draine, 1997). In published uses of the regression method, the direct-measure predictor is typically measured with error, violating the standard regression-analysis assumption of no measurement error in the predictor. In the presence of measurement error in the predictor, the intercept is overestimated, if (a) the true slope and (b) the mean of the predictor variable are both positive (Greenwald & Draine, 1997). In addition, Klauer, Draine, and Greenwald (in press) have shown that statistical tests for a positive intercept are also biased toward rejecting the null hypothesis such that α errors are inflated over their nominal values under these conditions.

This article summarizes a statistical approach that allows valid use of the regression method in the presence of typical measurement error on direct measures. For a detailed presentation of this method, see Klauer et al. (in press).

The Errors-in-Variables Method

A substantive assumption of the Greenwald et al. (1995) regression method is that the true predictor variable has a rational zero point and that its values are nonnegative. Consequently, the mean of the observed predictor variable is positive in most applications. In addition, the slope coefficients estimated in studies that employ the regression technique (Draine & Greenwald, 1998; Greenwald & Draine, 1997; Greenwald, Draine, & Abrams, 1996; Greenwald et al., 1995) are rarely negative such that the true slope parameters, which are systematically attenuated in the presence of error, are likely to be positive. The impact of these factors on regression coefficients and significance tests, however, is difficult to assess without an exact quantitative analysis.

There is a substantial body of literature about ways of correcting for measurement error in regression analyses, and many different kinds of methods have been proposed. Two methods are generally found most useful because they overcome many of the limitations of other methods (Plewis, 1985, chap. 5): the so-called errors-in-variables approach and structural-equation-modeling techniques.

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The *errors-in-variables approach* assumes normally and independently distributed true predictor and error variables. Under this model, the regression weights cannot be estimated, however, unless an additional piece of information over and above observed predictor and dependent variable is given. Fuller (1987, chap. 1), Isaac (1970), and Kendall and Stuart (1973, chap. 29), among others, summarize correction formulae for regression weights and their standard errors in situations with additional information. The most important cases are those in which (a) the measurement error variance in the predictor is known, (b) the ratio of error variances is known, or (c) the reliability of the predictor is given. Each of these cases is sufficient to make the model identified.

Such information is not available in the present research-oriented context, however, in which the predictor and the dependent variable are usually ad hoc operationalizations, for which separate reliability studies have not been performed. Another problem resides in the assumption of a normally distributed latent predictor, which is clearly violated here because the true predictor values are assumed to be nonnegative and may even take on the value zero with nonzero probability.

The *structural-equation-modeling approach* (Jöreskog, 1970; Sörbom, 1978) also defines the error-free predictor as a latent variable. This approach requires multiple indicators of the latent predictor variable, however, which are typically not available in research settings. In addition, the standard structural modeling approach assumes normally distributed latent predictors, which is an inappropriate assumption in the present context.

Klauer et al. (in press) have developed a model in the errors-in-variables framework that accommodates the assumption of a nonnegative latent predictor and requires no additional input over and above that used by the conventional regression analysis. The model takes as point of departure a standard errors-in-variables framework (Fuller, 1987, chap. 1.3), in which the true predictor variable as well as the error variables are independent and normally distributed random variables. For substantive reasons, however, the present situation requires that the true predictor variable (a) may assume only nonnegative values and (b) may take on the value zero with positive probability.

To accommodate the two requirements just stated, the latent predictor is assumed to follow a *truncated normal distribution* such that negative values are truncated and set to zero. Although many different distributional assumptions can be thought of that also accommodate nonnegative latent predictors, the truncated-normal assumption is defensible as deviating least from the widely accepted assumption of a normally distributed latent predictor that is routinely made in the errors-in-variables approach.

The resulting model thereby not only provides a more realistic description of the data, but is also identified such that corrected estimates of the regression estimates and their standard errors can be obtained without additional information. This new variant of the errors-in-variables approach has been realized as a FORTRAN computer program.[1] The algorithm takes a set of (x, y) pairs as input and outputs the corrected regression estimates and their standard errors, on which tests for significance can be based.

In a simulation study and in reanalyses of the data sets by Greenwald et al. (1995) as well as Draine and Greenwald (1998), Klauer et al. (in press) have demonstrated the usefulness of the proposed approach. Although these new analyses mostly confirm the original patterns of results obtained by means of the conventional regression approach, correcting for measurement error altered the results in some cases. In particular, in the Greenwald et al. (1995) data, the reanalysis obtained evidence of both indirect effects without direct effects (intercept > 0) as well as evidence of some degree of relation between direct and indirect effects (slope > 0), whereas the conventional analysis had revealed only the indirect-without-direct effect pattern (intercept > 0). For the Draine and Greenwald (1998) data sets, correcting significance tests for measurement error reduced the number of significant positive intercepts from 16 significant results to 11.

[1] Copies may be obtained from Karl Christoph Klauer.

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