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Impact of Assumption Violations on the Accuracy of Direct Range Restriction Adjustments

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IMPACT OF ASSUMPTION VIOLATIONS ON THE ACCURACY OF DIRECT RANGE RESTRICTION ADJUSTMENTS

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For decades researchers, analysts, and organizational professionals have utilized correction equations to adjust for the effects of various statistical artifacts. However, every correction method has certain assumptions that must be satisfied to work properly. These assumptions are likely rarely satisfied for range restriction corrections. As a result, these correction methods are used in a manner that can lead to incorrect results.

The current study employed a Monte Carlo design to examine the direct range restriction correction. Analyses were conducted to examine the accuracy of adjustments made with the direct range restriction correction when its assumption of perfect top-down selection was violated to varying degrees. Analyses were conducted on two datasets, each representing a population of 1,000,000 cases. The following variables were manipulated: the population correlation, the selection ratio, and the probability that the hypothetical applicant would accept the job if offered. Results of the accuracy of the direct range restriction correction equation for the optimal (all job offers accepted) versus realistic (job offers refused at various rates) conditions demonstrated small differences in bias for all conditions. In addition, small differences in squared bias were observed for most of these conditions, with the exception of conditions with both low selection ratios and low probabilities of job offer acceptance. In a surprising finding, the direct range restriction correction equation exhibited greater accuracy for realistic job offer acceptance (some job offers refused) than for optimal job offer acceptance (all offers accepted). It is

recommended that researchers further explore the violations of assumptions for correction methods of indirect range restriction as well.

Introduction

Personnel selection is an important function in organizations and has been a major area of study within the field of Industrial-Organizational Psychology for decades (Muchinsky, 2012; Schmidt & Hunter, 1998; Thorndike, 1949). The goal of any personnel selection effort is to hire workers who will be successful at a given job (Muchinsky, 2012). To determine who should be hired, organizations utilize a wide variety of methods to predict job performance (e.g., interviews, résumés, work sample tests, personality tests, general mental ability, and integrity tests).

Organizations employ industrial-organizational psychologists to identify tests that are likely to predict job performance successfully and to conduct studies to determine the accuracy of these tests at predicting job performance (American Psychological Association, 2015). Due to the implications for both theoretical development and applied usage, the accuracy of the estimation of the predictive accuracy is critical for not only industrial-organizational psychology but any field of science (Mendoza & Mumford, 1987). There are a number of statistical artifacts that influence the magnitude of the validity coefficient, making it difficult to obtain accurate estimates of the validity of the test (Schmidt, Hunter, & Urry, 1976). One of these statistical artifacts is range restriction. The purpose of this literature review is to describe the concept of range restriction and the equation used to correct for its effects. Initially, the conceptual background as well as the different types of range restriction that can occur will be explained. This is followed by the correction methods used by researchers to correct range restriction and the assumptions that underlie those corrections that are typically violated. Finally, I will discuss the outcomes from a study that was designed to explore the accuracy of one of the ways range restriction is corrected.

Range Restriction

Conceptual Background

Range restriction occurs when a researcher or practitioner imposes a set of conditions that limits the variability of scores to some fraction of what was originally observed (Raju & Brand, 2003; Wiberg & Sundström, 2009). Ultimately, range restriction is a term used in situations in which the variance on a selection measure is reduced. This reduction decreases the correlation observed between variables, a correlation that serves as an estimate of the predictor validity. Depending upon the selection procedures utilized, it is possible that range restriction can increase, decrease, or not affect the correlation at all; however, a decrease is what is observed under the type of restriction that occurs most frequently in personnel selection (Weber, 2001). As noted by Le and Schmidt (2006), range restriction is a pervasive problem in educational, psychological, and workplace applications of tests. Range restriction originates because researchers must try to estimate parameters of the unrestricted population when researchers have data from only a restricted population (Mendoza & Mumford, 1987; Schmidt, Oh, & Le, 2006).

To provide a more concrete situation to elaborate on range restriction and how it can apply, consider the following example. The validity of the American College Testing (ACT) for predicting future performance in college can only be estimated using samples of students who are *actually admitted* to college (i.e., the restricted sample). However, the ultimate goal is to estimate the validity of the ACT when it is applied to the applicant population, and low scoring applicants are not admitted to selective universities. Due to the effects of range restriction in this manner, the population of students admitted into the undergraduate program will typically have higher mean ACT scores as well as reduced standard deviations than those who apply to college. In order to estimate the validity of the applicant (unrestricted) population from the observed validity of the accepted (restricted) population, a researcher must correct for the specific type of range restriction on ACT scores (Schmidt et al., 2006; Sjöberg, Sjöberg, Näswall, & Sverke, 2012).

Finally, the type of range restriction that occurs, as well as the subsequent correction equation for the given type of range restriction observed, can determine the extent to which results will be impacted. There are two major types of range restriction to be discussed: direct and indirect range restriction. Direct range restriction has appeared more frequently in research and has a larger effect than indirect range restriction on predictor-criterion relationships (Sackett, Lievens, Berry, & Landers, 2007). Therefore, direct range restriction will be discussed first.

Direct Range Restriction

Direct (or explicit) range restriction occurs when applicants or participants are selected in a top-down manner on a particular test or on some variable, *X*, typically with the use of a cut-off score or other screening method (Roth, Van Iddekinge, Huffcutt, Eidson Jr., & Bobko, 2002; Wiberg & Sundström, 2009). To elaborate on this concept further, imagine that an organization tests applicants on general mental ability. Furthermore, applicants are hired in a top-down fashion based on the scores on this general mental ability. Low scoring applicants are not hired, and, thus, do not have job performance scores. A researcher can only compute the validity coefficient between general mental ability scores and the criterion (e.g., job performance) for those who are hired. Therefore, a restriction of range on the observed scores and available data occurs, thus lowering the correlation that is reported unless it is corrected by the researcher.

Indirect Range Restriction

The second type of range restriction is known as indirect range restriction. Indirect range restriction occurs when applicants or participants are selected on some third variable, *Z*, a variable that is correlated with the predictor variable (*X*) to some degree (Hunter, Schmidt, & Le, 2006; Schmidt, Shaffer, & Oh, 2008; Wiberg & Sundström, 2009). To illustrate the nature of indirect range restriction, consider two possibilities. If the correlation between *X* and *Z* is 1.0, then top-down selection on *Z* is identical to top-down selection on *X*, causing range restriction that is identical to direct range restriction on the correlation between *X* and *Y*. If the correlation between *X* and *Z* is 0.0, then top-down selection on *Z* causes no restriction on *X*, leaving the correlation between *X* and *Y* unaffected. From these extremes we can conclude that stronger correlations between *X* and *Z* lead to greater range restriction effects on the observed correlation between *X* and *Y*. Referring to the previous ACT/college performance example, indirect range restriction would occur if students were selected on a variable that is correlated with ACT scores (e.g., high school GPA).

Indirect range restriction also occurs when an organization incorporates a multiple-hurdle selection system where one or more predictors are administered before the actual predictor of interest in order to screen out applicants (Roth et al., 2002). For example, a general mental ability test and résumé check could be conducted by an organization to first screen applicants; this reduced applicant pool could then be tested with a structured interview for the final step of the employee selection process. Even if every person who completes the structured interview is hired, the variability of the interview scores has been indirectly restricted due to the previous selection on the other tests.

Correction Methods

Several correction methods for range restriction have been used over the past century, dating back to their introduction with Pearson's (1908) publication of the correction formulas (Sackett et al., 2007). Aitken (1934) and Lawley (1943) expanded upon Pearson's work to account for multivariate cases of range restriction, and Thorndike (1949) further refined the concepts of and equations for direct and indirect range restriction. Each of these researchers postulated their correction method based upon classical measurement theory. Classical measurement theory, or Bayesian statistical inference, tells us how knowledge about the value of some variable, *X*, changes as we obtain other information related to *X*; this theory aided in the development of equations that correct for correlations affected by range restriction with predictor and criterion variables (Iversen, 1984).

Gatewood, Feild, and Barrick (2011) identified at least eleven different scenarios for direct and indirect range restriction that can occur depending upon various conditions present. However, the majority of range restriction occurrences involve situations that are addressed by only three correction equations; these three situations are often referred to as "cases" from Thorndike's research (Thorndike, 1947, 1949). This trend of using Thorndike's three correction equations is important to note because if a researcher applies the wrong formula to a given situation, an incorrect adjustment (either an underestimate or overestimate of the true predictor validity) will result. To what extent the true validity is altered depends entirely upon the formula used by the examiner, as some formulas may be drastically more harmful than others and lead the examiner to reach erroneous conclusions (Alexander, Carson, Alliger, & Barrett, 1984).

Direct Range Restriction Correction

The first correction equation to be discussed is used to correct *univariate* range restriction, which is when restriction has occurred on only one variable. Pearson was the first to present this univariate correction formula in 1903, but Thorndike (1949) and Gulliksen (1950) modified the formula, and this version of the equation (i.e., Thorndike's Case 2) is still frequently used by researchers today (Hunter et al., 2006). This equation refers to the most basic form of range restriction: only two variables relevant to the validity study (*X* and *Y*), top-down selection was performed on one of the variables (*X*, the predictor variable), and the unrestricted variance is known for the selected variable. Note that in this formula, values for s_X (standard deviation), s_X^2 (variance), and r_{XY} (correlation between *X* and *Y*) come from the restricted population. Values for S_X, S_X^2 are from the unrestricted population. The equation to correct for the effects of direct range restriction is as follows:

$$R_{XY} = \frac{\left(\frac{S_X}{s_X}\right) r_{XY}}{\sqrt{\left[\left(\frac{S_X^2}{s_X^2}\right)-1\right] r_{XY}+1}}. \qquad (1)$$

The equation was described by Gulliksen (1950) as an equation of explicit selection (direct selection on *X*). However, this correction equation does not specify how selection actually occurred; for example, only individuals in the tails of the distribution may be selected, or either or both of the tails of a distribution may be truncated to some degree (Sackett & Yang, 2000). The direct range restriction correction equation has been shown to give a close estimate of the true correlation as long as the assumptions of linearity and homoscedasticity are satisfied (Wiberg & Sundström, 2009). Also, it has been noted that bivariate normality is a sufficient, albeit unrequired, assumption for this correction equation as well (Lawley, 1943).

Indirect Range Restriction Correction

The correction for indirect range restriction (Thorndike's, 1947, Case 3) is as follows:

$$R_{XY} = \frac{r_{XY} - r_{XZ}r_{YZ} + r_{XZ}r_{YZ}(S_Z^2/s_Z^2)}{\sqrt{[1 - r_{YZ}^2 + r_{YZ}^2(S_Z^2/s_Z^2)][1 - r_{XY}^2 + r_{XY}^2(S_Z^2/s_Z^2)]}} \tag{2}$$

In this scenario, subjects are selected based on *Z*, where *Z* is a third variable related in some degree to *X*, *Y*, or both; the values of both *X* and *Z* are available for the subjects who are in the restricted population (Sackett & Yang, 2000; Saupe & Eimers, 2010). Also, the values of s_{XY}, s_Y, s_{YZ}, S_{YZ}, r_{XY}, r_{XZ}, and r_{YZ} are known (Thorndike, 1949). The ultimate aim is to estimate the correlation between *X* and *Y* for the unrestricted population. This correction equation follows the same linearity and homoscedasticity assumptions as the direct range restriction correction equation.

Assumptions of Range Restriction Corrections

Both the direct and indirect range restriction equations assume linearity and homoscedasticity. The assumption of linearity is satisfied only when two variables, *X* and *Y* respectively, have a relationship that is linear throughout an entire range of scores; the assumption of homoscedasticity is when the variance of the residual scores is equal throughout the range of scores, including scores in the unrestricted population (Sackett & Yang, 2000). These two underlying assumptions are the most common to be involved in correction equations and must be satisfied for the correction equations to function as intended. However, there are two other assumptions that are just as important to address, but apply less frequently to correction equations because they are misinterpreted, checked incorrectly, or not considered by researchers when they choose a correction method to account for range restriction.

The first of these assumptions is the assumption of normality, which states that all variables of interest will be normally distributed (Lande & Arnold, 1983). The second is the assumption of selection, such that the researcher correctly utilized either perfect top-down selection (explicit) or incidental selection methods. The assumption for perfect top-down selection is that only one variable, *X*, is the direct selection variable to determine the relationship between *X* and *Y* instead of some other unspecified variable, *Z* (Linn, Harnisch, & Dunbar, 1981). Incidental selection is a similar process, but selection is performed on variable, *Z*, a variable that is correlated with *X*, *Y*, or both (Linn et al., 1981). Further support for the assumption of perfect top-down selection is offered by the alternate mathematical expression of range restriction, which allows range restriction to be expressed in terms of selection ratios (e.g., Schmidt et al., 1976). The assumption of perfect top-down selection is manifest in these instances; a selection ratio of ten percent is interpreted as indicating that the top ten percent of test takers were selected. From this perspective (range restriction as selection ratio), application of the direct range restriction correction to a random sample of ten percent of the test takers, a sample free from range restriction, would yield wildly inaccurate results.

Violation of Assumptions

Instances in which the researchers believe that they are dealing with direct range restriction, most, if not all, of the assumptions are not satisfied (Linn et al., 1981). As a result, researchers may not understand these subtle differences in range restriction and may utilize an inappropriate correction method for their investigations.

First, the direct range restriction equation is designed to correct for selection on one variable for which the unrestricted standard deviation is known. Typically, selection is on *X*, the test, and the unrestricted standard deviation is known for that variable. If the unrestricted variance is known only for the other variable that is not being selected upon (i.e., *Y*), then researchers would need to utilize a different correction equation, which is often referred to as Thorndike's Case 1 (Alexander et al., 1984). Given that the designation of which variables are labeled as *X* or *Y* is merely arbitrary on behalf of the researcher, the most important aspects to understand are (a) which variable is the selection variable and (b) for which variable the unrestricted variance is known. The classic direct range restriction correction equation (Equation 1 above) is designed for situations in which the unrestricted standard deviation is known for the selected variable.

Violations of linearity can also cause problems for range restriction corrections. It is rare for the relationship between *X* and *Y* to be perfectly linear, and it is not uncommon to find that the regression of *Y* on *X* flattens out for extreme *X* values (Gross & Fleischman, 1983). Thus, truncation of the range of scores can change the relationship shown between *X* and *Y* such that a linear relationship may or may not be observed in the restricted sample.

Homoscedasticity is another assumption whose violation affects the accuracy of the range restriction adjustment. Generally, when the assumption of homoscedasticity is violated the correction tends to be adequate unless it is violated in correspondence with a violation in linearity (Gross & Fleischman, 1983; Holmes, 1990). This assumption is due to the reoccurring trend in research that has demonstrated that correction equations are more easily affected by violations in linearity, while being more resistant to moderate or even significant departures from the assumption of homoscedasticity by itself (Greener & Osburn, 1979). However, correction equations are still utilized even with this knowledge because an uncorrected correlation coefficient is more biased than a corrected value (Gross & Kagen, 1983; Weber, 2001). Violations of homoscedasticity cause the restricted regression coefficient to be stronger or weaker than the unrestricted regression coefficient. This violation results in an over or under correction when the range restriction correction is applied.

Finally, there is one last issue regarding the assumption of selection, more specifically, regarding the actual methods of direct selection. Researchers and practitioners assume that they are selecting in a perfect top-down manner, which is an underlying premise of direct and indirect range restriction adjustments. However, unbeknownst to them, some unknown or unspecified variable(s) are actually in play that cause the assumption of perfect top-down selection to rarely, if ever, hold true. To demonstrate this claim, consider the following example: An organization wishes to select individuals to hire directly based on their scores on general mental ability (g). The organization makes job offers to the highest scoring on the test (i.e., top-down selection). Offers proceed, in descending order down the list, until all of the job openings are filled.

However, not all potential hires accept the job offer. The organization must now skip this person's score and select the next score on the list. Thus, the perfect top-down selection principle of direct selection is not held in this situation. Therefore, what they believe to be direct selection is actually an occurrence of *indirect* selection procedures. Any correction of the resultant correlation with the direct range restriction correction risks the introduction of additional error into the validity estimate.

The Current Study

The assumption of perfect top-down selection underlying the direct range restriction correction is likely violated in almost every application of the correction in applied practice. When these violations occur, they are often unnoticed by researchers, who may not understand the finer details regarding range restriction, and likely result in corrections that are inaccurate. The current study was designed to test whether violations of the perfect top-down selection assumption reduce the accuracy of correlations corrected with the direct range restriction correction equation.

Hypothesis: Greater deviations from perfect top-down selection will lead to reduced accuracy in adjustments for direct range restriction.

This study utilized a Monte Carlo design to test this hypothesis. A Monte Carlo design is optimal for this study as it allows researchers the means to generate large datasets with known parameters. Three variables were manipulated: the population correlation between X and Y, the selection ratio, and the probability that a hypothetical applicant will accept a position. Range restricted sample correlations were computed and adjusted with the direct range restriction equation. These adjusted correlations were then compared to the population correlation to assess the accuracy of the adjusted value under the various conditions.

Method

Population Generation

Two datasets, each representing a hypothetical population, were generated for the study. Each dataset consisted of 1,000,000 cases with scores on two variables representing predictor and criterion scores. The population correlation was set to be either .35 or .45, values chosen to represent typical correlations in applied settings. Means and standard deviations for each variable were set to zero and one, respectively. Applicant samples were randomly drawn from the population of 1,000,000 cases. Selection ratios were set to be either .10 or .33. Sample correlations were computed on a sample of 150 cases (i.e., selected cases). Given that 150 cases were to be selected from the applicant samples and given the selection ratios of .10 or .33, the applicant sample size was either 1500 or 450. The final manipulation was the probability that the hypothetical applicant would accept the job if offered: .5, .8, or 1.0. These three manipulated variables resulted in twelve conditions (2 x 2 x 3) for the experiment.

Procedure

The experiment was conducted with the following procedure:

1. A sample of either 450 or 1500 cases was randomly selected from the population.
2. Each case was assigned a dichotomous yes/no decision of job offer acceptance, corresponding to an acceptance probability of .5, .8, or 1.0.

3. The highest 150 scoring applicants were offered employment. Selected applicants who rejected the job offer were omitted, and lower scoring applicants were then offered the job.
4. The sample correlation was computed for the selected group.
5. The sample correlation was adjusted for the effects of direct range restriction with Equation 1.
6. The adjusted correlation was then compared to the population correlation; bias (population correlation – adjusted sample correlation) and squared bias (the squared value of bias) were computed.
7. From the same applicant sample used for the above range restriction conditions, a random sample of the applicants was selected to form a No Range Restriction baseline condition. Scores in this sample were correlated, and the correlation was subsequently compared to the population value. Bias and squared bias were computed.
8. The process described in Steps 1-7 was repeated 1000 times.
9. The results across the 1000 replications were averaged yielding a mean bias and a mean squared bias for each condition. Cohen's *d* was computed for various comparisons of the 12 different conditions to assess the magnitude of effects.

Results

Statistics

Within each of the 12 experimental conditions, mean bias and mean squared bias were computed for Perfect Top-Down selection, Imperfect Top-Down selection, and the No Range Restriction baseline condition.

Mean Bias and Mean Squared Bias

Mean bias and mean squared bias results for the twelve conditions are listed in Tables 1 and 2. Table 1 lists the mean and standard deviation of bias, and Table 2 lists the mean and standard deviation of squared bias.

Effect Size Analyses

Rather than compute significance tests for the comparisons, tests that have no meaning in a Monte Carlo analysis, the effect sizes of differences in bias and squared bias between various range restriction conditions were assessed using Cohen's *d*. Table 3 lists Cohen's *d* values for the differences in bias for the following comparisons: Perfect Top-Down versus No Range Restriction, Imperfect Top-Down versus No Range Restriction, and Imperfect Top-Down versus Perfect Top-Down. Given Cohen's (1988) standards for *d* (.2 is small, .5 is medium, and .8 is large) to interpret the magnitude of effects, effect sizes were small for all bias analyses.

Table 4 lists Cohen's *d* values for differences in squared bias. For the comparison of both range restriction conditions (Imperfect Top-Down and Perfect Top-Down) to the No Range Restriction condition, squared bias was moderate to strong (*d* values ranged from .39 to .81, with a median of .64). For the comparison of Perfect and Imperfect Top-Down conditions, squared bias differences were small except for conditions where the selection ratio and probability of job offer acceptance were low. Contrary to the hypothesis, squared bias was lower for Imperfect Top-Down selection than for Perfect Top-Down selection in these conditions. In summary, the hypothesis of the study was not supported; for the comparison of Imperfect Top-Down selection against Perfect Top-

Down selection, bias was similar in magnitude across all conditions and squared bias was either similar in magnitude or was lower for the former condition than for the latter.

Table 1

Mean and Standard Deviation of Bias

ρ_{xy}	SR	*p*	No Range Restriction		Perfect Top-Down (Adjusted)		Imperfect Top-Down (Adjusted)	
			M	*SD*	*M*	*SD*	*M*	*SD*
0.35	0.33	0.5	-0.001	0.073	0.007	0.126	-0.006	0.097
0.35	0.33	0.8	0.004	0.074	0.009	0.132	0.009	0.125
0.35	0.33	1.0	0.002	0.070	0.008	0.129	0.008	0.129
0.35	0.10	0.5	0.001	0.072	0.011	0.163	0.015	0.141
0.35	0.10	0.8	0.002	0.073	0.009	0.162	0.004	0.155
0.35	0.10	1.0	0.000	0.073	0.009	0.164	0.009	0.164
0.45	0.33	0.5	-0.001	0.064	0.008	0.116	0.003	0.092
0.45	0.33	0.8	0.003	0.067	0.008	0.115	0.014	0.108
0.45	0.33	1.0	0.000	0.065	0.009	0.117	0.009	0.117
0.45	0.10	0.5	0.000	0.065	0.018	0.146	0.010	0.128
0.45	0.10	0.8	0.001	0.064	0.017	0.140	0.018	0.141
0.45	0.10	1.0	0.001	0.067	0.009	0.140	0.009	0.140

Note. For all conditions, the number of applicants selected was 150. Bias equals the difference between the population correlation and the sample correlation. Table results are the average across 1000 replications.

Table 2

Mean and Standard Deviation of Squared Bias

ρ_{xy}	SR	*p*	No Range Restriction		Perfect Top-Down (Adjusted)		Imperfect Top-Down (Adjusted)	
			M	*SD*	*M*	*SD*	*M*	*SD*
0.35	0.33	0.5	0.005	0.007	0.016	0.023	0.010	0.014
0.35	0.33	0.8	0.005	0.008	0.018	0.024	0.016	0.024
0.35	0.33	1.0	0.005	0.007	0.017	0.025	0.017	0.025
0.35	0.10	0.5	0.005	0.008	0.027	0.044	0.020	0.029
0.35	0.10	0.8	0.005	0.008	0.026	0.040	.0240	0.036
0.35	0.10	1.0	0.005	0.008	0.027	0.037	0.027	0.037
0.45	0.33	0.5	0.004	0.006	0.013	0.021	0.008	0.013
0.45	0.33	0.8	0.005	0.007	0.013	0.023	0.019	0.020
0.45	0.33	1.0	0.004	0.006	0.014	0.020	0.014	0.020
0.45	0.10	0.5	0.004	0.006	0.022	0.039	0.017	0.027
0.45	0.10	0.8	0.004	0.006	0.020	0.030	0.020	0.030
0.45	0.10	1.0	0.004	0.006	0.020	0.030	0.020	0.030

Note. For all conditions, the number of applicants selected was 150. Squared bias equals the squared difference between the population correlation and the sample correlation. Table results are the average across 1000 replications.

Table 3

Effect Size Estimates for Differences in Bias

ρ_{xy}	SR	*p*	Cohen's *d* Perfect Top-Down vs. No Range Restriction	Imperfect Top-Down vs. No Range Restriction	Imperfect Top-Down vs. Perfect Top-Down
0.35	0.33	0.5	0.08	-0.06	-0.12
0.35	0.33	0.8	0.04	0.05	0.00
0.35	0.33	1.0	0.06	0.06	0.00
0.35	0.10	0.5	0.08	0.12	0.03
0.35	0.10	0.8	0.06	0.02	-0.03
0.35	0.10	1.0	0.06	0.06	0.00
0.45	0.33	0.5	0.10	0.05	-0.05
0.45	0.33	0.8	0.06	0.12	0.05
0.45	0.33	1.0	0.10	0.10	0.00
0.45	0.10	0.5	0.17	0.10	-0.06
0.45	0.10	0.8	0.15	0.15	0.00
0.45	0.10	1.0	0.07	0.07	0.00

Table 4

Effect Size Estimates for Differences in Squared Bias

ρ_{xy}	SR	*p*	Cohen's *d*: Perfect Top-Down vs. No Range Restriction	Cohen's *d*: Imperfect Top-Down vs. No Range Restriction	Cohen's *d*: Imperfect Top-Down vs. Perfect Top-Down
0.35	0.33	0.5	0.62	0.39	-0.34
0.35	0.33	0.8	0.67	0.56	-0.08
0.35	0.33	1.0	0.64	0.64	0.00
0.35	0.10	0.5	0.69	0.71	-0.18
0.35	0.10	0.8	0.72	0.73	-0.05
0.35	0.10	1.0	0.81	0.81	0.00
0.45	0.33	0.5	0.61	0.43	-0.29
0.45	0.33	0.8	0.51	0.49	-0.07
0.45	0.33	1.0	0.63	0.63	0.00
0.45	0.10	0.5	0.62	0.63	-0.15
0.45	0.10	0.8	0.73	0.73	0.01
0.45	0.10	1.0	0.69	0.69	0.00

Discussion

Range Restriction vs. No Range Restriction Comparisons

The results of the study indicate two main outcomes regarding corrections for direct range restriction in optimal conditions (all job offers accepted; i.e., perfect top-down selection). First, bias for any type of range restriction was only incrementally greater (maximum Cohen's d = .12) than bias for the no range restriction condition. Second, squared bias was greater in the range restriction conditions than for the no range restriction condition; effect sizes were moderate to large in magnitude (median Cohen's d = .64). Thus, even when corrected, range restriction introduces error (greater average deviations from the population correlation) into the estimate of the population correlation. (As a final note to comparisons to the No Range Restriction condition, the correlations in the No Range Restriction condition were also adjusted with the direct range restriction correction. Results for all comparisons were nearly identical to those for the unadjusted No Range Restriction. In addition, differences in bias and squared bias between the adjusted and unadjusted No Range Restriction were trivial, with all Cohen's d values less than .10. Given that the results were nearly identical to the unadjusted No Range Restriction condition, this adjusted No Range Restriction condition will not be discussed further.)

Perfect vs. Imperfect Top-Down Range Restriction

The purpose of this study was to determine whether violations of the assumption of perfect top-down selection reduce the accuracy of the direct range restriction correction equation. Bias differences were extremely small (greatest Cohen's d = .12) between Perfect and Imperfect Top-Down range restriction in all conditions. For squared bias, Cohen's *d* was extremely small for 10 of the 12 conditions. However, for two conditions (p = .5 and SR = .33 at both population correlation levels), squared bias was -.34 and -.29, with the Imperfect Top-Down selection exhibiting lower levels of squared bias than the Perfect Top-Down selection. This finding was somewhat counterintuitive, as the opposite effect (greater bias with more exceptions to perfect top-down selection) was hypothesized. Therefore, to further explore this finding, two more conditions were tested with even lower probabilities of acceptance (p = .33). For the first condition, the selection ratio was set to .33 and the population correlation (ρ_{xy}) was set to .35. Bias differences were very small in this condition (Cohen's *d* = -.10), whereas squared bias differences were moderate to large (Cohen's d = -.70). For the second condition, the selection ratio was set to .33 and the population correlation (ρ_{xy}) was set to .45. As before, bias differences were small (Cohen's *d* = -.09), whereas squared bias differences were moderate (Cohen's *d* = -.59). Thus, the only observed differences in the accuracy of the direct range restriction adjustment for perfect versus imperfect top-down selection occurred when the selection ratio and the probability of job offer acceptance were low. As before, adjustments were more accurate (i.e., reduced squared bias) when selection was not perfect top-down. These results indicate that researchers have little to fear concerning the accuracy of the direct range restriction adjustment when selection is not of a perfect top-down nature, as is the case in applied situations.

Limitations and Future Research

The selection ratios, population correlations, and probabilities of acceptance that were used for the study were chosen in an attempt to be reflective of realistic conditions. However, researchers and practitioners may find that actual conditions markedly differ from these values. Future studies may wish to extend this study to address values for the manipulated variables that were not modeled in this study.

Conclusions

In most conditions, there were no differences in the accuracy of the direct range restriction correction between perfect (all job offers accepted) and imperfect (some job offers refused) top-down selection. In situations where there is a difference in accuracy between the two conditions (low selection ratio and low probabilities of job offer acceptance), the direct range restriction correction equation provides a more accurate population correlation when top-down selection is imperfect (i.e., the assumption of perfect top-down selection is not supported) than when top-down selection is perfect. Therefore, researchers who wish to utilize the direct range restriction correction have little to fear regarding its accuracy when selection is not of a perfect top-down nature.

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