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The Effects of Imperfect Top-Down Selection on the Accuracy of the Direct Range Restriction Adjustment

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THE EFFECTS OF IMPERFECT TOP-DOWN SELECTION ON THE ACCURACY OF THE DIRECT RANGE RESTRICTION ADJUSTMENT

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ABSTRACT

THE EFFECTS OF IMPERFECT TOP-DOWN SELECTION ON THE ACCURACY OF THE DIRECT RANGE RESTRICTION ADJUSTMENT

Accurate assessment of the effectiveness of personnel psychology functions is vital to the field. Many personnel decisions are made based on correlations between predictor variables and measures of job performance; however, those correlations are often affected by range restriction. As encountered in applied practice, range restriction weakens the strength of the correlation. Equations exist to correct for the effects of range restriction on correlations; these equations are widely accepted and used by Industrial-Organizational psychologists today. This study expands on research by Hall (2016), which examined the accuracy of the direct range restriction correction equation provided by Thorndike (1949) under varying degrees of the violation of the assumption of perfect top-down selection. A Monte Carlo analysis was conducted so that the adjusted sample correlations could be compared to known, unrestricted population correlations. The results of the study indicate that Thorndike's correction equation provides adjusted sample correlations that were closer to the true population correlation when perfect top-down selection does not occur. Implications and recommendations for future research are discussed.

Keywords: *range restriction, top-down selection*

DEDICATION

I dedicate this thesis to my husband. Words cannot express the depth of love, support and patience he has shown to me over the last few years, and especially this past year as I have finished my thesis and degree. He has been a constant source of encouragement and cheer, and I am truly blessed to have him by my side.

I dedicate this also to my parents, who always taught me to never give up. Their support has been abundant and cherished. They have bolstered me in the valleys and celebrated with me on the hilltops. The love and support they have shown me over the years cannot be described. I am truly blessed to be their child.

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When making personnel decisions, it is vital to have evidence supporting those decisions. Data analysis plays a key role in many functions within the field of Industrial-Organizational (IO) psychology. However, a poorly considered application of statistical analysis procedures can lead to incorrect conclusions. Many personnel decisions, particularly when it comes to selection, are made based on the correlation between two variables, *X* and *Y*. If *X* is found to predict *Y*, a relevant criterion measure, then the organization would have support for selection decisions based on scores on *X* (SIOP, 2018). Correlations in the selection context are subject to distortion from statistical artifacts. One statistical artifact that can greatly affect the strength of correlations calculated by IO psychologists and practitioners is range restriction. This study will investigate the extent to which the violation of the assumption of perfect top-down selection affects the accuracy of equations designed to correct for range restriction.

Literature Review

Range Restriction

Range restriction occurs when the range of a sample taken from a population represents only a portion of the population, and not the entire range of the population. One cause of range restriction is pre-selection on the basis of a variable being studied (Raju & Brand, 2003; Ree et al., 1994). Depending on the selection procedures used, range restriction may greatly affect the strength of the correlation between two measures. Depending on the nature of the restriction, range restriction can have little effect or even increase the correlation (Cascio, 1991), but what is most frequently observed in the context of selection measures in personnel decisions is a reduction in the strength of the correlation (Salkind, 2010). Range restriction is a commonly observed phenomenon in IO psychology and personnel practice, and there are two main types of range restriction, direct and indirect.

Direct Range Restriction

Direct range restriction occurs when selection decisions are made based on the same variable in the correlation being studied. In other words, the range of scores on X (scores which will be correlated with Y) is restricted on the basis of X because X was used as a basis for selection. This selection results in all scores in a dataset under or above a certain cutoff being removed from the dataset. An example commonly used to illustrate direct range restriction is the correlation of scores on college entrance exams and performance in college. For example, high school students take the SAT in preparation for college applications. A university may choose to only admit students who score at least a 1000 on the SAT. After those students complete some time in the university, students' academic performance during their time at the university is measured. This measure of academic performance is used to calculate a correlation with SAT scores. However, the range of the scores included in the correlation has been restricted because only students who were admitted into the university (i.e., only students who scored at least a 1000 on the SAT) would have obtained a score on the academic performance measure. The range has been *directly* restricted because SAT scores were used as the basis for selection into the university. University officials, when making the decision to set a cutoff for SAT scores, were likely assuming that higher SAT scores would be correlated with higher academic performance in college. Yet, by setting a cutoff score for entrance into the university, they have no way of truly knowing whether that assumption holds true for the entire range of SAT scores.

Indirect Range Restriction

Indirect range restriction has less obvious effects on the dataset and is more commonly encountered in applied settings. Indirect range restriction occurs when selection decisions are made on the basis of a third variable, *Z*, a variable that is also correlated with the predictor and criterion variable. This selection results in changes in the distributions of the predictor and/or criterion variable, thus altering the observed sample correlation (Beatty et al., 2014). Indirect range restriction affects the correlation coefficient to the extent that the third variable is correlated with the predictor and/or criterion variable (Guion, 1998). Because *Z* is used as the selection variable, and *Z* is correlated with *X* and *Y*, scores on *X* and *Y* are more likely to be missing below a certain point. In other words, indirect range restriction results in a thinning of the data, particularly on the low end (assuming positive correlations and selection at the top end of Z) of the range of *X* and *Y* values. For this reason, selection on the basis of a third variable is often referred to as *incidental selection*. "Incidental selection...occurs when it is possible to observe an individual at any point on the variable, but the probability that an observation is lost from the sample is related to the variable itself" (Sackett & Yang, 2000, p. 112).

Both indirect and direct range restriction result in the observed correlation being weaker than the population correlation. Sackett and Yang (2000) show the effects of different types of range restriction on the sample correlation. In their simulations, if the population correlation (ρ_{XY}) is .5, direct truncation on *X* or *Y* below the mean resulted in a reduction of the correlation (r_{XY}) to .33. However, when truncation occurred on the basis of a third variable (*Z*), correlated with both *X* and *Y* at .5, the resulting correlation with the restricted sample was reduced to .41. This correlation of the restricted sample is notably higher than the correlation resulting from direct range restriction; however, it is still substantially lower than the population correlation.

Range Restriction Corrections

Given the effects of range restriction on the strength of correlation coefficients and the importance of accurately estimating correlations for personnel decisions, the need for a method of correcting for those discrepancies is manifest. Correction equations for range restriction were introduced by Pearson (1903) and were subsequently refined by Thorndike (1949). It is the correction equations presented by Thorndike that are still widely used in psychometric study and practice today; these equations will be the focus of the present study.

Correction equation for direct range restriction

The equation provided by Thorndike to correct for direct range restriction is commonly referred to as "Thorndike's Case II" correction. In this case, the estimate of the unrestricted sample correlation between *X* and *Y* can be expressed as

$$R_{xy} = \frac{\left(\frac{S_x}{s_x}\right) r_{xy}}{\sqrt{\left[\left(\frac{S_x^2}{s_x^2}\right) - 1\right] r_{xy}^2 + 1}}$$

where S_x is the standard deviation of the unrestricted sample, s_x is the standard deviation of the restricted sample, S_x^2 is the variance for the unrestricted sample, and s_x^2 is the variance for the restricted sample. The formula, therefore, uses the ratio of unrestricted to restricted standard deviation (or variance as need be) of *X*, the selection variable, multiplied by the restricted sample correlation to estimate the unrestricted sample correlation.

Correction equation for indirect range restriction

The equation used to estimate the unrestricted sample correlation from a sample that has been subject to indirect range restriction is as follows:

$$R_{xy} = \frac{r_{xy} - r_{xz}r_{yz} + r_{xz}r_{yz}\left(\frac{S_z^2}{s_z^2}\right)}{\sqrt{\left[1 - r_{yz}^2 + r_{yz}^2\left(\frac{S_z^2}{s_z^2}\right)\right]\left[1 - r_{xy}^2 + r_{xy}^2\left(\frac{S_z^2}{s_z^2}\right)\right]}}$$

This formula is used when neither *X* nor *Y* is used as a selection variable, but instead a third variable *Z* is used to select from the sample. This formula was also provided by Thorndike (1949), and situations where the sample has been restricted in this manner are commonly referred to as "Thorndike's Case III." In this case, the correlations between *X* and *Z* and between *Y* and *Z*, and between *X* and *Y* are known for the restricted sample, and they are all used in the formula, along with the variance of *Z*, the selection variable, for the restricted (s_z^2) and unrestricted (S_z^2) samples, to estimate the unrestricted correlation between *X* and *Y*.

Assumptions for Range Restriction Corrections

According to Lawley (1943), the accuracy of the correction equation for direct range restriction depends on two properties: linearity of the relationship between *X* and *Y*, and the homoscedasticity of variance of *Y* for the entire range of *X* values. The assumption of linearity is satisfied when the relationship between *X* and *Y* remains linear throughout the range of scores. The assumption of homoscedasticity is satisfied when the variance of residuals is constant across the range of scores for each variable. According to Wiberg and Sundström (2009), as long as those two assumptions are satisfied, the correction equations for direct and indirect range restriction yield close estimates of the true correlation between *X* and *Y*.

However, there are two other assumptions for range restriction correction equations that are sometimes overlooked when estimating the correlation for the unrestricted sample from a restricted sample. The first is *bivariate normality*. This assumption is one that is required for the interpretation of correlations in general, and it is satisfied when both variables *X* and *Y* have a normal distribution, and, furthermore, when the joint distribution of the two variables is normally distributed (Wolfe & Schneider, 2017). The second assumption that underlies the correction equations for both direct and indirect range restriction is the assumption of perfect top-down selection. For example, if the selection ratio were set to .10, then the top 10% of scorers on *X* would be selected; these test takers, and only these test takers, have scores on *Y*. In the context of a hiring decision, for example, that would mean that if 100 applicants applied for a position, the ten most qualified (i.e., the applicants with the ten highest scores on *X*) would be selected for the job *and would accept the job offer*. This assumption is often violated in practice. Acceptance of a job offer varies depending on economic conditions, the type of job, location, and a myriad of other factors. And whereas selection in the real world almost never occurs in a perfect top-down manner, the direct range restriction equation is often the one that is used to estimate the correlation of the unrestricted sample.

Hall (2016) conducted a study examining the accuracy of correlations corrected for direct range restriction in the face of violations to the assumption of perfect top-down selection. Hall (2016) used a Monte Carlo analysis in which he manipulated the unrestricted population correlation (.35 or .45), the selection ratio (.10 or .33), and the probability that a selected applicant would accept the job offer (.5, .8, and 1.0). Hall then compared the corrected correlations to the true unrestricted population correlations and used Cohen's *d* values to interpret the magnitude of differences between the corrected correlations and the true correlations. Contrary to his hypothesis, he found that, while both range restriction conditions (i.e., Perfect Top-Down selection and Imperfect Top-Down selection) yielded moderate to strong measures of bias when compared to the no range restriction condition (with Cohen's *d* values for squared bias between .39 to .81), the differences between the Perfect and Imperfect Top-Down selection conditions were often slight.

The Present Study

In this study, I will extend Hall's (2016) analysis of the effectiveness of the direct range restriction correction to cover a situation in which the probability of job offer acceptance is even lower at .2 and .4. I will also address a slightly higher probability of acceptance (one not covered by Hall) of .6.

Hypothesis: As the deviation from perfect top-down selection increases, the accuracy of the direct range restriction adjustments will decrease.

Method

A Monte Carlo analysis is a type of research that allows researchers to determine the accuracy of statistical procedures using large datasets with a variety of known parameters. Thus, researchers can identify conditions in which the procedure works as intended as well as conditions in which it does not. Monte Carlo analyses are useful for testing the effectiveness of correlation adjustment equations because they allow for researchers to compare the adjusted correlation to a known unrestricted population value.

Two datasets containing 1,000,000 cases each were created with two scores for each case representing scores on a predictor and criterion variable. The scores were set such that one dataset had a population correlation of .35 and the other had a population correlation of .45. For the sake of standardization and simplicity, means for all scores in the study were set to zero and standard deviations wereset to one. As in Hall's (2016) study, selection ratios of .10 and .33 were included in the study. Because the selected sample size was 150, random samples of 450 and 1500 cases were drawn from the population for the job applicant sample. Each case within the sample was assigned a dichotomous yes/no decision to reflect acceptance probabilities of .2, .4, .6, and 1.0. The highest 150 scores that were assigned a "yes" decision were included in the sample to represent applicants who were offered the job and accepted it. Sample correlations were then corrected with the direct range restriction equation. It is important to note that the selection ratio of .33 was not tested with the acceptance rate of .2 because doing so would not have provided enough selected applicants who accepted the job to fill all 150 positions.

Procedure

Using SAS® software, two populations of 1,000,000 cases each were generated with each case representing a job applicant and having a score on two variables, both of which have a standard normal distribution. The two variables had a correlation of .35 in one population and .45 in the other population. From each population, a sample of 450 cases and a sample of 1,500 cases were randomly selected. The cases within each sample were assigned a dichotomous decision of yes or no corresponding to a probability of .2, .4, .6, or 1.0 to represent the applicants' acceptance of the job offer. Applicants with the highest 150 scores on the X variable were offered employment. Selected applicants who rejected the job offer were omitted, and lower scoring applicants were then offered the job until the 150 openings were filled. The sample correlation (r_{xy}) was then computed for the selected group, and the sample correlations were adjusted for the effects of direct range restriction using Equation 1. Next, adjusted sample correlations were compared to the population correlation by computing bias (population correlation minus adjusted sample correlation) and squared bias (the squared value of bias). A random sample of applicants was selected from the same applicant samples used for the range restriction conditions to form a no range restriction condition which was used as a baseline condition. Scores in this sample were correlated, and the sample correlation was compared to the population correlation by computing bias and squared bias.

This process was repeated 1,000 times, and results from the 1,000 replications were averaged to yield a mean bias and a mean squared bias for each condition. Cohen's *d* values were then computed for various comparisons of the different conditions to assess the magnitude of effects.

Results

Table 1 shows that the no range restriction condition produced correlations that averaged to values very close to the actual population correlations. As would be expected given the nature of the range restriction, the unadjusted correlations were lower (greater deviation from the population value) for the theoretical top-down condition than for the realistic top-down condition.

Table 1

Mean Correlation Coefficients by Condition

ρ	SR	AR	No RR	Theoretical Top-Down	Real Top-Down	Theoretical Top-Down (Adjusted)	Real Top-Down (Adjusted)
.35	.10	.6	.351	.151	.167	.336	.344
		.4	.348	.157	.181	.347	.342
		.2	.348	.145	.219	.322	.345
	.33	.6	.350	.193	.228	.342	.345
		.4	.351	.195	.282	.343	.347
.45	.10	.6	.447	.199	.221	.430	.439
		.4	.446	.205	.243	.439	.445
		.2	.447	.197	.289	.428	.442
	.33	.6	.448	.259	.301	.444	.444
		.4	.445	.254	.368	.438	.445

Note. Table entries are the mean values across 1,000 samples. ρ = population correlation. SR = selection ratio. AR = acceptance rate (the probability of accepting a job offer). No RR represents results from the no range restriction condition. Theoretical Top-Down is pure top-down selection where all job offers are accepted. For Real Top-Down the probability of acceptance of a job offer equals the value in the AR column.

The adjusted correlation results ran counter to my hypothesis; upon correction for direct range restriction the realistic top-down values were at least as accurate as those for the theoretical top-down condition. In short, not only did the violation of the assumption of perfect top-down selection fail to reduce the accuracy of the direct range restriction correction, it increased the accuracy in some conditions. These findings are shown in Table 2 for bias (mean difference between population correlation and adjusted correlation) and Table 3 for squared bias (mean squared difference).

Because bias for a given sample could be positive or negative, the mean bias values shown in Table 2 are not as useful as the mean squared bias values shown in Table 3. Squaring the bias for each sample before finding the mean eliminates the possibility of positive and negative bias values canceling out each other. As expected, the theoretical top-down conditions yielded greater levels of bias than the realistic top-down conditions. The greatest differences occurred for the samples with the lowest acceptance rates. For each of those four conditions, the mean squared bias for the theoretical top-down condition was more than double the mean squared bias for the realistic top-down condition. Furthermore, it is interesting to note that the mean squared bias was fairly consistent among conditions with the same population correlation and selection ratio for the theoretical top-down condition. In other words, the acceptance rate had virtually no effect on the amount of bias found. However, for the realistic top-down condition, the mean squared bias varied systematically in conjunction with the acceptance rate. For each combination of correlation and selection ratio, higher acceptance rates yielded higher levels of bias.

Table 2

Means and Standard Deviations of Bias

ρ	SR	AR	No Range Restriction		Theoretical Top-Down (Adjusted)		Real Top-Down (Adjusted)	
			$\bar{X}$	S	$\bar{X}$	S	$\bar{X}$	S
.35	.10	.6	-0.001	0.072	0.014	0.172	0.006	0.149
		.4	0.002	0.071	0.002	0.164	0.008	0.146
		.2	.002	0.071	.028	0.166	.005	0.112
	.33	.6	0.000	0.072	0.009	0.130	0.006	0.107
		.4	-0.001	0.073	0.008	0.131	0.003	0.085
.45	.10	.6	0.002	0.067	0.019	0.149	0.010	0.133
		.4	0.004	0.066	0.010	0.145	0.005	0.126
		.2	0.003	0.067	0.022	0.147	0.008	0.100
	.33	.6	0.001	0.064	0.006	0.111	0.005	0.096
		.4	0.005	0.067	0.012	0.115	0.005	0.077

Note. Table entries are the mean values across 1,000 samples. ρ = population correlation. SR = selection ratio. AR = acceptance rate (the probability of accepting a job offer). No RR represents results from the No Range Restriction condition. Theoretical Top-Down is pure top-down selection where all job offers are accepted. For Real Top-Down the probability of acceptance of a job offer equals the value in the AR column.

Table 3

Means and Standard Deviations of Squared Bias

ρ	SR	AR	No Range Restriction		Theoretical Top-Down (Adjusted)		Real Top-Down (Adjusted)	
			$\bar{X}$	S	$\bar{X}$	S	$\bar{X}$	S
.35	.10	.6	0.005	0.007	0.030	0.042	0.022	0.032
		.4	0.005	0.007	0.027	0.038	0.021	0.034
		.2	0.005	0.007	0.028	0.043	0.013	0.017
	.33	.6	0.005	0.007	0.017	0.025	0.011	0.017
		.4	0.005	0.008	0.017	0.025	0.007	0.010
.45	.10	.6	0.004	0.006	0.022	0.036	0.018	0.027
		.4	0.004	0.007	0.021	0.037	0.016	0.025
		.2	0.004	0.007	0.022	0.036	0.010	0.014
	.33	.6	0.004	0.006	0.012	0.018	0.009	0.014
		.4	0.004	0.007	0.013	0.021	0.006	0.009

Note. Table entries are the mean values across 1,000 samples. ρ = population correlation. SR = selection ratio. AR = acceptance rate (the probability of accepting a job offer). No RR represents results from the No Range Restriction condition. Theoretical Top-Down is pure top-down selection where all job offers are accepted. For Real Top-Down the probability of acceptance of a job offer equals the value in the AR column.

Extended comparisons of bias and squared bias are shown in Tables 4 and 5 which compare bias and squared bias for the adjusted values to the bias and squared bias observed in the no range restriction condition. These comparisons take the form of Cohen's *d* statistic, which translates mean differences into a standardized metric of number of standard deviations. Table 4 shows that bias was low for both adjusted values (*d* less than .2 in all conditions) but was slightly lower for the realistic top-down adjusted values (less than .1) than for the theoretical top-down condition. Table 5 shows higher levels of squared bias in *d* terms (*d* ranges from .5 to .8), but *d* values are generally lower for realistic top-down.

Table 4

Cohen's d for Bias

ρ	SR	AR	Theoretical Top-Down (adj) vs. No Range Restriction	Real Top-Down (adj) vs. No Range Restriction
.35	.10	.6	0.114	0.060
		.4	0.000	0.052
		.2	0.204	0.032
	.33	.6	0.086	0.066
		.4	0.085	0.050
.45	.10	.6	0.147	0.076
		.4	0.053	0.010
		.2	0.166	0.059
	.33	.6	0.055	0.049
		.4	0.074	0.000

Note. ρ = population correlation. SR = selection ratio. AR = acceptance rate (the probability of accepting a job offer). No Range Restriction represents results from the no range restriction condition. Theoretical Top-Down is pure top-down selection where all job offers are accepted. For Real Top-Down the probability of acceptance of a job offer equals the value in the AR column.

Table 5

Cohen's d for Squared Bias

ρ	SR	AR	Theoretical Top-Down (adj) vs. No Range Restriction	Real Top-Down (adj) vs. No Range Restriction
.35	.10	.6	0.830	0.734
		.4	0.805	0.652
		.2	0.747	0.615
	.33	.6	0.654	0.462
		.4	0.647	0.221
.45	.10	.6	0.697	0.716
		.4	0.638	0.654
		.2	0.694	0.542
	.33	.6	0.596	0.464
		.4	0.575	0.248

Note. ρ = population correlation. SR = selection ratio. AR = acceptance rate (the probability of accepting a job offer). No Range Restriction represents results from the No Range Restriction condition. Theoretical Top-Down is pure top-down selection where all job offers are accepted. For Real Top-Down the probability of acceptance of a job offer equals the value in the AR column.

Conditions with the higher correlation and the higher proportion of applicants chosen from the sample (i.e., ρ = .45, *SR* = .33) and the lowest acceptance rates for realistic top-down conditions yielded bias values that were essentially no different from bias found in the no range restriction condition. But, as mentioned before, due to the possible presence of both positive and negative bias values and their ability to cancel each other out when calculating the mean, it is beneficial to look more closely at the Cohen's *d* values for squared bias, shown in Table 5. Table 5 shows the same patterns that were found in Table 3. Differences for squared bias varied in conjunction with the acceptance rate for the realistic top-down conditions. That is, for conditions that had the same population correlation and selection ratio, higher acceptance rates yielded greater differences in squared bias and lower acceptance rates yielded smaller differences in squared bias when comparing the realistic top-down conditions to the no range restriction condition. Cohen's *d* values for squared bias comparing the theoretical top-down conditions to the no range restriction condition did not display this same pattern. The lowest differences in squared bias occurred for conditions with the lowest acceptance rates for each combination of population correlation and selection ratio in the realistic top-down conditions.

Discussion

These results are interesting, given the underlying assumption of perfect top-down selection in using the direct range restriction correction equation. The results of the present study indicate that the direct range restriction correction yields results that are actually more accurate when perfect top-down selection is not observed than when it is observed. However, it is important to note that this study used the observed (i.e., actual) standard deviations in the correction equation. There is, however, and alternate method to execute the direct range restriction correction that uses the selection ratio instead of the observed standard deviations. This approach is often employed in meta-analyses. For example, in a meta-analysis, actual standard deviations may not be known, so researchers will use the selection ratios, which are (sometimes) known, to estimate the restricted and unrestricted standard deviations. To convert a selection ratio to the restricted standard deviation (where the unrestricted standard deviation is 1.0), the following equation is employed (Schmidt, Hunter, & Urry, 1976, p. 485).

$$SD_{res} = \sqrt{1 + \frac{z}{\left(e^{z^2/2}\sqrt{2\pi}\right) * SR} - \left(\frac{1}{\left(e^{z^2/2}\sqrt{2\pi}\right) * SR}\right)^2}$$

where SR is the selection ratio and z is the value from a standard normal distribution that corresponds to a probability of $1 - SR$. The equation above assumes perfect (i.e., theoretical) top-down selection. Although the current study did not provide evidence that imperfect top-down selection diminishes the accuracy of the direct range restriction correction equation, if the study had utilized estimates of standard deviation based on the equation above, rather than actual standard deviations, the results may be different. More research is needed to explore this topic.

Conclusion

The results of this study show that researchers and practitioners need not fear using the direct range restriction equation when selection did not occur in a perfect top-down fashion as long as the range restriction adjustment is made with the actual (i.e., observed) standard deviations. The error (bias and squared bias) is no worse in cases where perfect top-down selection does not occur than when perfect top-down selection does occur. In fact, the results of this study indicate that the correction equation for direct range restriction yields an adjusted correlation that is slightly more accurate when perfect top-down selection is not present. This finding is good news for the field as perfect top-down selection is likely never encountered in practice due to organizational consideration of multiple factors in the selection process as well as the existence of multiple employment options for highly desired candidates.

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