Multiple Regression in Industrial Organizational Psychology: Relative Importance and Model Sensitivity

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Abstract

When evaluating research findings, it is important to examine what statistical methods were used to reach and support the stated conclusions. Regression is a common analysis in the Industrial/Organizational psychology literature and researchers have debated how to interpret the standardized optimal weights produced in ordinary least squares (OLS) regression. Multiple methods for determining the relative importance of predictors in a regression model have been proposed, along with a variety definitions of what is meant by predictor importance. Conversely, it has been shown that by slightly decreasing the model R^2 that is obtained through OLS multiple regression an infinite number of alternative weight vectors can be produced, calling into question the meaning of OLS weights when the alternative weights diverge from the OLS weights. Articles published from 2003-2014 in the *Journal of Applied Psychology*, *Academy of Management Journal, and Psychological Science* that used OLS regression were reviewed. It was found that regression is used to answer questions on a wide variety of topics and interpreted in a multitude of ways in the I/O psychology and general psychology literature. The study found that different relative importance analyses can result in different conclusions about what predictors are most important. Examining alternative weight vectors further brings into question conclusions drawn based on optimal weights. For the majority of studies examined alternative weight vectors were found that provided a different rank ordering of predictors with only a small loss in model fit. The findings in this paper highlight and reinforce the need for Industrial/Organizational psychologists to turn a critical eye on the interpretation of regression analyses, especially regression weights, in reaching substantive conclusions.

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1 Introduction

It has become clear in Industrial/Organizational (I/O) psychology that, not only is it important to carefully consider what topics warrant future study, but also to give deliberate thought to how to study the selected topic of interest. There appears to be a delay between the publication in quantitative psychology journals of new information regarding statistical analysis methods favored by Industrial/Organizational psychologists, and the acceptance and implementation of these findings by those publishing in premiere I/O journals. A prime example is the continuing controversy regarding the use of null hypothesis significance testing and psychologists' abilities to correctly interpret and communicate the findings of their statistical analyses (e.g. Cohen, 1994; Cortina & Landis, 2011; Schmidt, 2010).

Dissemination of relevant findings from cutting edge quantitative journals (e.g., *Psychometrika*) to I/O psychology is crucial for informing correct use and interpretation of statistical tools in the I/O field. Critical flaws in widely used statistical approaches can have a profound effect on I/O knowledge and applications. Ignoring methodological advancements can compromise the integrity of I/O psychologists' work. The overall objective of the current research is to critically examine the use of multiple regression analysis in a sample of recently published I/O research leveraging developments from the quantitative literature demonstrating fundamental problems with regression weights. This analysis will yield an enhanced understanding of how to interpret regression analyses and ensure that conclusions based on these analyses are sound.

Ordinary least squares (OLS) multiple regression is a frequently used statistical approach in I/O psychology (Stone-Romero, Weaver, & Glenar, 1995; O'Neill, McLarnon, Schneider, & Gardner, 2013). Peer reviewed journal articles and field applications use regression to test hypotheses about the relative importance of predictor variables. The field's guidelines (Principles for the Validation and Use of Personnel Selection Procedures (Society for Industrial and Organizational Psychology, 2003)) presume the use of multiple regression analyses in providing evidence for important issues relating to prediction, fairness and bias. In short, multiple regression has been embedded in the DNA of both applied and academic I/O psychologists.

OLS multiple regression is used to determine which linear combination of independent variables results in the smallest sum of squared errors (SSE) when predicting the dependent variable; it also maximizes the correlation between observed and predicted values of the dependent variable. The combination of weights that produce this minimized SSE and maximized correlation are considered optimal. In this paper beta weights will refer to the standardized regression weights calculated based on a sample of data. It long has been known that, when developing a regression equation for the purpose of predictive power outside of the original sample, equal weights perform as well as optimal weights in some situations (e.g., Davis-Stober, 2011; Green, 1977; Ree, Carretta, & Earles, 1998; Schmidt, 1971; Wainer, 1976; Wilks, 1938).

Waller (2008) demonstrated that there are an infinite number of interchangeable weights that produce a proportion-of-variance-accounted-for just slightly smaller than the maximized squared multiple correlation. That is, infinite sets of exchangeable (or Waller states, "fungible") regression weights in multiple regression all result in the same, slightly suboptimal variance-accounted-for. Waller further illustrated that the fungible solutions may drastically differ from each other and from the least squares weights. This last point raises major concern for the interpretation of regression weights.

The practice of interpreting regression weights in research and applied settings appears to have critical flaws. Thus, interpreting regression weights is not as direct as has been portrayed in applied psychology research and practice. For example, journal articles that have drawn conclusions based on the size or relative magnitude of regression weights need to be examined carefully as they may be endorsing erroneous conclusions based on optimal weights.

These erroneous conclusions are not only a threat to those conducting I/O psychology research but also to consumers of research who may reach incorrect conclusions and practitioners who may base applications on faulty interpretations. Currently, much research in I/O psychology uses multiple regression analysis and many articles using this method are highly influential. Waller's (2008) demonstration of how some regression models are insensitive to changing multiple regression weights and the misleading conclusions than can result from relying on these weights have not been fully recognized and integrated in the I/O field. It is crucial to bridge this divide between the applied and quantitative literature.

In order to bridge the divide, research must highlight how findings regarding statistical methods presented in quantitative journals have a direct impact on the validity of the conclusions being drawn in applied journals. Analyzing the use of multiple regression weights in I/O research will help I/O psychologists appreciate the limitations of the approach and may lead to different substantive conclusions than those already reported in the literature.

Understanding what regression weights actually mean is essential before conclusions are drawn. Koopman (1988) found that, at least in some situations, similar composites (which, in terms of multiple regression, would be considered the predicted criterion values) could be produced by weights that differ from the optimal weights but that similar weights cannot produce drastically different composites. It follows then that when examining multiple regression, the interpretation of the obtained optimal weights can pose a challenge. When determining how to interpret regression weights, it is important to examine parameter sensitivity. Parameter sensitivity is determined by examining how changes in weights are related to changes in fit indices (e.g., SSE and R^2 values). Models that are sensitive to weight shifts are characterized by a large change in fit indices accompanied by small changes in the weights; the fit indices associated with models that are insensitive to weight fluctuations are robust to slight (and sometimes not so slight) changes in weights.

It is important to make the distinction between sampling variability and parameter sensitivity. Large samples and meta-analysis have allowed I/O psychologists to become increasingly confident in their findings. Large sample sizes help to protect analyses from sampling variability that arises from capitalization on chance. Sampling variability is how parameter estimates might change across samples. Statistical significance is linked to sampling variability. Sampling variability is a valid consideration that has received much attention, but it is not the only consideration. Parameter sensitivity has been a less prevalent topic in I/O literature and is actually independent of sample size (Green, 1977). The lack of a relationship between parameter sensitivity and sample size is important because the general approach of bigger is better when considering sample size will not help to protect statistical results against parameter sensitivity.

Parameter sensitivity highlights the difficulty in deriving meaning from beta weights in OLS regression. Various issues related to interpreting beta weights have been examined over the years and many methods have been proposed as improvements over beta weights when it comes to determining relative importance of predictors. Dominance analysis, relative weights analysis, and various other methods have made strides towards comparing the relative importance of predictors in a regression model (Johnson & Lebreton, 2004; Nimon & Oswald, 2013). Unfortunately, despite being discussed within the psychology literature, some believe that the lack of metrics provided in the standard SPSS regression output contribute to researchers relying on beta weights and R^2 (e.g. Nathans, Oswald, & Nimon, 2012; Nimon, 2011). Even with the advantages offered by relative importance analytical methods, these methods do not result in a measure of the overall model sensitivity. A measure of regression model sensitivity is absent from the I/O literature and would allow a more complete understanding of regression analysis. Understanding methods we employ will allow us to make more valid conclusions and provide better recommendations for practice.

The current research on how to interpret multiple regression weights is compelling. Unfortunately, this research has not made it into the mainstream I/O journals, despite the use of an I/O article to illustrate the points made in Waller (2008) and calls for psychologists to attend to the quantitative literature (Nimon, 2011). In order to strengthen the dissemination of and attention to new statistical findings by I/O researchers and practitioners, it is important to emphasize their direct applicability and critical importance to I/O psychology.

The current research has descriptive rather than inference-based goals. Well-defined methods already exist to determine if multiple regression models are insensitive. It is also clear that, when models are insensitive, and even when they are not, it is difficult to draw conclusions from their relative magnitude. This study draws upon two complementary lines of existing research - the more theoretical quantitative research on fungible weights and the applied research in I/O psychology. Specifically, the following questions will be addressed:

1. How is regression used in I/O and general psychology and how are regression weights interpreted?

2. What analyses have been used in the I/O and general psychology literature to interpret beta weights in regression?

3. Are regression models in the I/O and general psychology literature insensitive to shifts in predictor weights?

4. How influential are the I/O and general psychology articles that use OLS regression?

Taken together, the answers to these questions will describe the magnitude of problems arising from reliance on regression weights in the I/O and general psychology research literature. Examining the insensitivity of multiple regression weights used in research will allow I/O researchers to understand the magnitude of the impact of improperly interpreting regression weights specifically and statistical tools more generally. In this paper the notation of Abadir and Magnus (2002) is used, vectors are represented by bold-italic lowercase letters, matrices are represented as bold-italic uppercase laters, and random variables and scalars are represented by italic lowercase letters.

1.1 Regression in I/O Research

Regression has had a robust presence in I/O research. Stone-Romero et al. (1995) examined research published in the *Journal of Applied Psychology* between 1975 and 1993. They found that, across this time period, between 10% and 38% of articles employed multiple regression. Also during this time frame, the proportion of articles using multiple regression increased.

The applications of regression can be split into two distinct categories: prediction and explanation (Courville & Thompson, 2001). Regression has been used heavily to support and reject theories, and has played a major role in the selection literature. The literature examining general mental ability (g) as a predictor of job performance has repeatedly used regression to emphasize the role of g in prediction even when other selection tools are employed.

Schmidt and Hunter (1998) conducted a meta-analysis and summarized 85 years of research in personnel selection. They used regression to identify predictors that added incremental validity above g when predicting job performance and training performance. Work samples, integrity tests, structured interviews, and conscientiousness measures added the most incremental validity when they were combined with g in a regression. This regression analysis also showed that, if g is used in a selection system, unstructured interviews add only .04 to the validity of the system. Regression also identified measures of conscientiousness and integrity tests as the two predictors that added the most incremental validity above g when predicting training performance. The impact of this article was enormous, as it was cited over 3,500 times according to Google Scholar (as of February 24, 2017).

Schmidt and Hunter (2004) re-examined past findings on personality and g to determine which variables measured early in life were most important in predicting career success later in life. In this study, they re-analyzed data from Judge, Higgins, Thoresen, and Barrick (1999) using multiple regression. They combined occupational level and income into a variable titled career success. The adjusted multiple R for when Big Five personality traits were included in the model was .56. After adding g into the model, the multiple R raised to .63. Schmidt and Hunter examined the beta weights and concluded that g and conscientiousness were the most important predictors. Another regression was run with only g and conscientiousness as predictors, and the multiple R remained at .63. This study emphasized the fact that measures of cognitive ability maintain their validity over the long term, with scores obtained in childhood predicting outcomes years later.

Ree, Earles, and Teachout (1994) used multiple regression to examine findings concerning specific abilities (s) and g. They found that adding s into a regression only increased the validity of the system by .02 over g. Their findings indicated that, although s does add validity in predicting performance, the addition is small and may not be considered worthwhile in some contexts.

Leadership is a popular research topic and there has been controversy over whether traits are useful in the context of leadership. Bass (1990) posed the question of what differentiates leaders from other people. Judge, Bono, Ilies, and Gerhardt (2002) conducted a meta-analysis to look at predictors related to leadership. They used meta-analytic correlation estimates to conduct a regression to examine how the Big Five predicted leader emergence and leadership effectiveness. They found that the multiple R for predicting leadership emergence from the Big Five was .53 and for predicting leadership effectiveness was .39. Extraversion, conscientiousness, and openness were the strongest predictors of leadership. This study confirmed that personality is a useful predictor of leadership, both emergence and effectiveness. It also highlights that personality may be more relevant to emergence than to effectiveness.

A newer interest in personnel selection is changes in criteria over time, and whether or not predictors will remain valid across these changes in the criteria of interest. Lievens, Ones, and Dilchert (2009) examined the validity of the Big Five personality factors for predicting performance across multiple years of medical school. They used meta-analytic correlation estimates to regress performance on the Big Five. They found that, across the years of medical school, the beta weights increased for extraversion, openness, agreeableness, and conscientiousness. The largest gains were seen in openness, extraversion, and conscientiousness. They attributed this gain to the change in what was being captured by the selected criteria (GPA). The authors believe that performance in applied settings became more important, and the need for interpersonal skills increased. This study emphasized the importance of criterion change. It also highlighted the importance of personality for predicting long-term success in the medical field and other fields where interpersonal skills become increasingly important as time goes on.

1.2 Regression in Applied Domains

Not only has regression been a popular tool in academic research, but it is often used in applied settings as well. In applied settings, regression is frequently used in developing and evaluating selection systems, determining what factors influence things like employee engagement and performance, and evaluating the effectiveness of various intervention programs. When working as an external consultant, the question often faced is, "Will the consultant increase the company's prediction capabilities?" In this case, hierarchical regression may be used to demonstrate whether combining existing predictors with a new, customized measure would allow the client to better predict which applicants will perform well on the job.

When working within a company, there might be a more general question, such as, "What measures should the company use to screen and hire applicants for a particular position?" In this situation a few measures may be administered to incumbents and the incumbents' performance evaluation can be used as the outcome variable. The multiple R can be examined to determine the validity of the combined measures. Regression also can be used to eliminate measures that are not contributing to the prediction of the criterion. If a measure is removed from the regression equation and the multiple R does not change much, then it may not be worthwhile to administer that assessment. It is also possible to break down the performance evaluation into sub-scales and use each subscale as a dependent variable. If the multiple R is particularly low for one subscale, then efforts can be focused on developing a new selection measure that would better predict performance in this area.

Another question in applied settings that is targeted using multiple regression is: "What drives employee engagement and turnover?" Many companies administer surveys at least once a year that gauge employee engagement and/or satisfaction. Regression sometimes is used to examine which items, or subscales, are most predictive of future employee satisfaction or turnover. Given the dichotomous outcome variable, predicting turnover within the year would involve using a logistic regression procedure. Standard OLS regression is often used when looking at how responses to an engagement survey at time 1 might account for responses to survey questions such as "Do you intend to stay?" and "What is your overall satisfaction with your job?" at time 2. Using regression, companies attempt to determine what issues are most likely to cause employees to leave, become disengaged, or less productive members of the team. The company may decide to change a policy or launch interventions as a result of these analyses.

2 Brief Review of Relevant Regression Literature

2.1 Multiple Regression

OLS multiple regression is used to create a linear composite of a specified set of predictor variables that minimizes the sum of squared errors (SSE) when predicting the outcome variable. This process maximizes the correlation between the observed and predicted values of the outcome variable. The combination of weights that produce this minimized SSE and maximized correlation is considered optimal.

The general (model) form of OLS multiple regression is:

$$\boldsymbol{y} = b_0 + b_1\boldsymbol{x}_1 + b_2\boldsymbol{x}_2 + \ldots + b_p\boldsymbol{x}_p + \boldsymbol{e}$$

where $\boldsymbol{y}$ is an $n \times 1$ vector of scores on the outcome variable of interest. b_0 is the intercept value, which can be thought of as what the score on $\boldsymbol{y}$ would be if all $\boldsymbol{x}_i$ were equal to 0. Each $\boldsymbol{x}_i$ is an $n \times 1$ vector of scores on predictor variable i. The predictor variables can also be represented as an $n \times p$ matrix, $\boldsymbol{X}$, of predictor scores. The regression weights associated with each predictor are represented by b_1 through b_p. Error in the model is represented by the $n \times 1$ vector $\boldsymbol{e}$ and is often referred to as random error. The error can be from random influences or from variables unaccounted for in the model. The takeaway from the model is that in OLS regression $\boldsymbol{y}$ is assumed to be a linear combination of p predictors and error (Bobko, 2001; Darlington, 1968).

There are a few important assumptions surrounding the error term. The error is assumed to be conditionally normally distributed with a mean of 0 and a constant variance across all values of $\boldsymbol{x}_i$. Sources of error (which can be thought about as separate $\boldsymbol{e}_i$) are assumed to be independent (Bobko, 2001).

The model discussed above is a theoretical population model. When creating a model in practice the error term is not estimated and we are left with:

$$\hat{\boldsymbol{y}} = \hat{b}_0 + \hat{b}_1\boldsymbol{x}_1 + \hat{b}_2\boldsymbol{x}_2 + \ldots + \hat{b}_p\boldsymbol{x}_p.$$

Here, $\hat{\boldsymbol{y}}$ is the $n \times 1$ vector of predicted values of $\boldsymbol{y}$ based on the regression equation and and each $\hat{b}_i$ is the estimated regression weight associated with predictor p. When scores on all variables are standardized so that their variance is equal to one, and centered so the their mean is equal to 0, then the regression weights become standardized regression coefficients, called beta weights. If the scores are standardized and centered at 0 (converted to z-scores), the intercept term disappears. This standardized regression form is:

$$\hat{\boldsymbol{y}} = \boldsymbol{X\beta}.$$

Where $\boldsymbol{\beta}$, is the $p \times 1$ vector of standardized regression coefficients, β_1 through β_p.

2.2 Determining Importance in Multiple Regression

In the past, researchers have used a variety of methods to evaluate the contribution of predictors, including zero-order correlations, standardized beta weights, and semipartial correlations (Budescu 1993; Johnson, 2000; Johnson & LeBreton, 2004; Tonidandel, LeBreton, & Johnson, 2009). However, these measures are not easy to interpret when multicollinearity exists, which is often (if not always) the case in I/O psychology (Darlington, 1968). When variables are uncorrelated, the zero-order correlations and standardized beta weights are equivalent and the sum of their squares is equal to the multiple R^2; this equivalence is no longer true when predictors are correlated. It has been recommended that regression coefficients and correlations be taken into account when trying to determine relative importance. However, simply examining these two indices is subjective and leaves room for debate (Courville & Thompson, 2001; Johnson & LeBreton, 2004; Thompson & Borrella, 1985). To complicate the matter, it is possible for a predictor to have a large correlation with the outcome variable but have a beta weight near 0, or even a large positive correlation with the criterion and a negative beta weight (Darlington, 1968).

One of the major issues in determining the relative importance of predictors in a regression equation is defining importance (Nathans, Oswald, & Nimon, 2012; Johnson & LeBreton, 2004; LeBreton, Ployhart, & Ladd, 2004; Budescu 1993). Different measures use different definitions of importance to rank-order variables. LeBreton et al. (2004) proposed that measures of relative importance could assess direct effects, total effects, and partial effects. It is important to note that the definitions of direct, total, and partial effects used by LeBreton et al. and throughout the rest of this paper differ from how these terms are commonly defined in structural equation modeling (SEM) (e.g. Sobel, 1990). LeBreton et al. define direct effects as the contribution of a predictor to the outcome variable without the presence of other predictors. A predictor's total effect is its contribution after the contributions of all other predictors have been removed. The partial effects focus on a predictor's contribution when accounting for some type of model subset(s).

A single technique can assess more than one type of importance based on this classification system. Looking at all three types of effects for a predictor gives a more complete picture of how that predictor functions within the system. Beta weights only account for total effects. Given that they are calculated by taking into account the contributions of all predictors, they do not reflect partial or direct effects (Nathans et al., 2012).

2.2.1 Zero-Order Correlation Coefficients

Zero-order correlation coefficients, also known as validities, are the correlations between the predictors and the outcome variable. They are measures of the direct effect of the predictor on the outcome variable and do not account for the effects of other predictors (Nathans et al., 2012). They are easy to calculate and even can be calculated by hand in small data sets. The zero-order correlation is simply the covariance of the predictor and outcome variable divided by the product of the two variables' standard deviations. For this paper the zero-order correlation for a given predictor, x_i, will be denoted $r_{\boldsymbol{y}\boldsymbol{x}_i}$.

When predictor variables are uncorrelated, the squared zero-order correlations of all predictor variables with the outcome variable sum to R^2. If the question facing a researcher or practitioner is, "Which single predictor should I use?" then it makes sense to choose the predictor with the largest zero-order correlation since shared variance with other predictors is not a concern. However, when looking at questions concerning which predictors should be used together, zero-order correlations can be hard to interpret in the presence of correlated predictors.

2.2.2 Standardized Regression Weights

Standardized regression weights (beta weights) are the weights obtained from an OLS regression where the predictor and criterion have been transformed into z scores. Along with interpreting their relative size, researchers often report the statistical significance of the beta weights. The significance of a beta weight is generally determined using a t-test, and simply states whether or not the beta weight significantly differs from 0 (Bobko, 2001). The commonly used formulas for determining the significance of a single unstandardized predictor weight can be expressed as:

$$t(n-p-1) = \frac{b_i}{s_{b_i}}.$$

$$s_{b_i}^2 = \frac{s_{\boldsymbol{y}}^2(1-R^2)}{s_{\boldsymbol{x}_i}^2(1-R_i^2)(n-p-1)}.$$

Where R_i^2 is the R^2 obtained from regressing predictor x_i onto all other predictors in the model. As R_i^2 increases, so does $s_{b_i}^2$, indicating that with increasing multicollinearity amongst predictors the regression weights become more unstable. Remember that in the case of beta weights scores on the predictors and the outcome variable have been converted to z-scores. It follows that for beta weights s_y^2 and $s_{x_i}^2$ will be equal to 1 and can be removed from the calculation for $s_{b_i}^2$ (e.g. Harris, 2001). This means the equations can be rewritten as:

$$t(n-p-1) = \frac{\beta_i}{s_{\beta_i}}.$$

$$s_{\beta_i}^2 = \frac{(1-R^2)}{(1-R_i^2)(n-p-1)}.$$

It is important to note that Jones and Waller (2013) found that under certain conditions using the above formula to compute the standard error for a given β_i produced biased results, and suggested that users of regression should use the delta method to estimate the standard error for a given β_i.

Regression weights represent the expected difference in the outcome variable, given an increase of one unit in the predictor, while holding the value of other predictors constant (Hoyt, Leierer, & Millington, 2006). Interpreting the relative size of beta weights is often used to assess variable importance (Thompson, 2001; Zientek, Capraro, & Capraro, 2008).

2.2.3 Structure Coefficients

Structure coefficients examine direct effects by looking at the correlation between a predictor and the score on the outcome variable predicted by the full regression model ($\hat{\boldsymbol{y}}$) (Courville & Thompson, 2001; LeBreton, Ployhart, & Ladd, 2004):

$$r_{S_i} = r_{\hat{\boldsymbol{y}}\boldsymbol{x}_i}.$$

Dunlap and Landis (1998) demonstrate that structure coefficients can also be calculated by dividing the zero-order correlation by the multiple R for the regression model:

$$r_{S_i} = \frac{r_{\boldsymbol{y}\boldsymbol{x}_i}}{R}.$$

In order to see how $r_{\hat{\boldsymbol{y}}\boldsymbol{x}_i}$ is equivalent to $\frac{r_{\boldsymbol{y}\boldsymbol{x}_i}}{R}$ let $\boldsymbol{X}$ be the $n \times p$ matrix of standardized scores (z scores) for all n subjects on p predictor variables. Let $\boldsymbol{\beta}$ be the $p \times 1$ column vector of standardized OLS regression weights and let $\hat{\boldsymbol{y}}$ be the $n \times 1$ column vector of predicted criterion scores. Given $\hat{\boldsymbol{y}} = \boldsymbol{X}\boldsymbol{\beta}$, we know that:

$$\text{Cov}(\boldsymbol{X}, \hat{\boldsymbol{y}}) = \text{Cov}(\boldsymbol{X}, \boldsymbol{X}\boldsymbol{\beta}).$$

Which means that:

$$\mathrm{Cov}(\boldsymbol{X}, \hat{\boldsymbol{y}}) = \left(\tfrac{1}{n-1}\right) \boldsymbol{X'X\beta}.$$

Given that:

$$\boldsymbol{R_X} = \left(\frac{1}{n}\right) \boldsymbol{X'X},$$

where $\boldsymbol{R_X}$ is the predictor correlation matrix. The $\mathrm{Cov}(\boldsymbol{X}, \hat{\boldsymbol{y}})$ can be expressed as:

$$\mathrm{Cov}(\boldsymbol{X}, \hat{\boldsymbol{y}}) = \boldsymbol{R_{XX}\beta}.$$

In order to convert $\mathrm{Cov}(\boldsymbol{X}, \hat{\boldsymbol{y}})$ to $\boldsymbol{r_{\hat{y}X}}$, it is necessary to divide $\mathrm{Cov}(\boldsymbol{X}, \hat{\boldsymbol{y}})$ by the square root of the variance of $\hat{\boldsymbol{y}}$. The variance of $\hat{\boldsymbol{y}}$ can be calculated as:

$$s^2_{\hat{\boldsymbol{y}}} = \mathrm{E}(\hat{\boldsymbol{y}}^2) - [\mathrm{E}(\hat{\boldsymbol{y}})]^2.$$

Since $\mathrm{E}(\hat{\boldsymbol{y}})$ is equal to 0 this can be reduced to:

$$s^2_{\hat{\boldsymbol{y}}} = \mathrm{E}(\hat{\boldsymbol{y}}^2).$$

It then follows:

$$\mathrm{E}(\hat{\boldsymbol{y}}^2) = \left(\tfrac{1}{n}\right) \sum \hat{\boldsymbol{y}}^2$$

$$\left(\frac{1}{n}\right) \sum \hat{\boldsymbol{y}}^2 = \left(\frac{1}{n}\right) \boldsymbol{\beta' X' X \beta} = \boldsymbol{\beta' R_X \beta}.$$

Putting it all together we see that:

$$\boldsymbol{r_{\hat{y}X}} = \frac{\boldsymbol{R_X\beta}}{\sqrt{\boldsymbol{\beta' R_X \beta}}}.$$

Noting that:

$$\boldsymbol{\beta} = \boldsymbol{R}_{\boldsymbol{X}}^{-1}\boldsymbol{r}_{y\boldsymbol{X}},$$

it follows:

$$\boldsymbol{r}_{\hat{y}\boldsymbol{X}} = \frac{\boldsymbol{R}_{\boldsymbol{X}}\boldsymbol{R}_{\boldsymbol{X}}^{-1}\boldsymbol{r}_{y\boldsymbol{X}}}{\sqrt{\boldsymbol{\beta}'\boldsymbol{R}_{\boldsymbol{X}}\boldsymbol{R}_{\boldsymbol{X}}^{-1}\boldsymbol{r}_{y\boldsymbol{X}}}} = \frac{\boldsymbol{r}_{y\boldsymbol{X}}}{\sqrt{\boldsymbol{\beta}'\boldsymbol{r}_{y\boldsymbol{X}}}}.$$

Given that $R^2 = \boldsymbol{\beta}'\boldsymbol{r}_{y\boldsymbol{X}}$:

$$\boldsymbol{r}_{\hat{y}\boldsymbol{X}} = \frac{\boldsymbol{r}_{y\boldsymbol{X}}}{R}.$$

Structure coefficients are simply correlations, and squaring structure coefficients represents the variance shared between the estimate of the outcome variable and the score on a predictor variable. Looking at structure coefficients in conjunction with beta weights can be enlightening. A variable with a large structure coefficient and small beta weight must share common variance with the outcome variable with at least one other predictor. One or more other predictors are accounting for that shared variance in the regression model (Nathans et al., 2012).

Structure coefficients can also be used to detect suppressor variables. If a predictor has a large beta weight and a small structure coefficient, that variable is a suppressor variable. However structure coefficients cannot identify which predictors are being suppressed nor the size of the suppression effect (Nathans et al., 2012).

2.2.4 Pratt Measure

Pratt (1987 as cited in Nimon & Oswald, 2013 and Thomas, Hughes, & Zumbo, 1998) developed a measure referred to as the Pratt measure or product measure. It is calculated as follows:

$$m_i = \beta_i r_{\boldsymbol{y}\boldsymbol{x}_i}.$$

Where m_i is the value of the Pratt measure for predictor i. As can be seen above, this measure is the product of the standardized regression coefficient for predictor i and the zero-order correlation between scores on predictor i and the outcome variable $\boldsymbol{y}$. It is a decomposition of R^2 and the m_i's sum to R^2. Given the nature of the calculation, this measures both direct (zero-order correlation) and total effects (beta weights) (Nathans et al., 2012).

This measure of variable importance is fascinating in that it allows importance to be calculated for a subset of variables simply by adding their individual importance scores. Difficulties of interpretation for this measure arise when a negative or zero value of m_i is observed, which can be a result of correlated predictors or suppression effects (Thomas et al., 1998).

2.2.5 Commonality Analysis

Commonality coefficients partition the variance explained in the regression model into unique effects and common effects. Unique effects apply to a single predictor while common effects come from variance shared by every possible subset of predictors (Amado, 1999; Nathans et al., 2012; Zientek & Thompson, 2006).

Unique effects are a measure of total effect. They quantify the contribution of a predictor to the model that is not shared with other predictors. It is also known as the predictor's usefulness or squared semipartial correlation. In the case where all predictors are uncorrelated, the unique effect is equivalent to the squared zero-order correlation and squared beta weight. In the case of uncorrelated predictors, ranking of variable importance can be done based on the unique effects (Nathans et al., 2012). Common effects are also a measure of total effect and measure the predictor's contribution that that predictor shares with every possible predictor set. For a three predictor model, seven commonality coefficients would be calculated. Three commonality coefficients would be calculated for the unique contribution of each predictor and then four commonality coefficients would be calculated for the four, two-predictor subsets.

Commonality analyses can be particularly useful in identifying suppressor effects (Nimon & Oswald, 2013; Zientek & Thompson, 2006). While a small negative commonality coefficient can be a result of sampling error, negative commonality coefficients can also indicate the presence of a suppressor. Commonality analysis allows suppression effects to be quantified by summing the negative common effects (Nimon & Oswald, 2013).

2.2.6 Dominance Analysis

Budescu (1993) set out three conditions for determining the relative importance of predictors in a regression equation:

> "(a) Importance should be defined in terms of a variable's "reduction of error" in predicting the criterion, y; (b) The method should allow for direct comparison of relative importance instead of relying on inferred measures; (c) Importance should reflect a variable's direct effect (i.e. when considered by itself), total effect (i.e., conditional on all other pre-

dictors), and partial effect (i.e. conditional on subsets of predictors)." (Budescu, 1993, p.544).

Note that Budescu does not assume that variables can be ordered in terms of importance. Dominance analysis sets out to determine if ranking by importance can occur (Johnson & LeBreton, 2004).

Dominance analysis compares pairs of predictors and how they behave in $h = 2^{(p-2)}$ models. These models involve all subsets of predictors. Variable a dominates variable b in model h if adding variable a to model h results in a greater R^2 than adding variable b to model h. By performing a dominance analysis for all pairs of the p predictors, dominance analysis determines an order of importance for the predictors, if that order exists.

Azen and Budescu (2003) defined three levels of dominance: complete, conditional, and general. Variable a completely dominates variable b if it is dominant across all h models. Variable a conditionally dominates variable b if the average increase in resulting from the addition of variable a across models of size k is greater than that for variable b for all k. Variable a generally dominates variable b if the average increase in R^2 caused by the addition of variable a across all h models is greater than that for variable b.

Dominance analysis becomes computationally difficult as the number of predictors in the model increases. For a 10 predictor model, 256 models must be computed, this number rises to 262,144 models in the case of 20 predictors. Even with modern computers this process can be prohibitive due to memory and time requirements. Let's think about a company with a 21 item engagement survey, 20 items are considered possible drivers of engagement and one item is a general engagement question that is seen as the outcome variable of interest. The company wants to know the "key drivers" of that single outcome item by examining the relationship of the 20 items at time 1 to the outcome item at time 2. That immediately involves the aforementioned 262,144 models, assuming only company wide results are required. Now suppose someone asks how that same analysis would look for the sales, HR, and engineering functions? This would require running 4 dominance analyses with 20 predictors- that is over 1 million models. And this does not even take into account regional stakeholders.

2.2.7 Relative Weights

Noting the computational challenges of dominance analysis as the number of predictors increased, Johnson (2000) proposed a method of relative importance analysis that examines total effects (Nathans et al., 2012). Relative weights analysis involves deriving a set of variables that are uncorrelated with each other but that maximize the correlation with the initial predictors (Tonidandel & Lebreton, 2010). The goal is to find the best-fitting set of orthogonal variables in the least squares sense, where the SSE between the original and orthogonal variables is minimized. Finding the orthogonal variables starts with the singular value decomposition of $\boldsymbol{X}$, where $\boldsymbol{X}$ is an $n \times p$ matrix of predictor scores. The decomposition is as follows:

$$\boldsymbol{X} = \boldsymbol{P}\boldsymbol{\Delta}\boldsymbol{Q}'.$$

Where $\boldsymbol{P}$ is an $n \times p$ matrix containing the eigenvectors of $\boldsymbol{X}\boldsymbol{X}'$ that correspond to the nonzero eigenvalues, $\boldsymbol{Q}$ is a $p \times p$ matrix of the eigenvectors of $\boldsymbol{X}'\boldsymbol{X}$, and $\boldsymbol{\Delta}$ is diagonal and contains the singular values of $\boldsymbol{X}$. The set of orthogonal variables that minimizes the residual sum of squares between the original and orthogonal variables is contained in matrix $\boldsymbol{Z}$:

$$\boldsymbol{Z} = \boldsymbol{P}\boldsymbol{Q}'.$$

After finding the orthogonal variables, standardized beta weights are obtained from regressing $\boldsymbol{y}$ on $\boldsymbol{Z}$. The vector of beta weights from this regression is given by the following:

$$\boldsymbol{\beta}^* = \boldsymbol{Q}\boldsymbol{P}'\boldsymbol{y}.$$

Next, $\boldsymbol{X}$ is regressed on $\boldsymbol{Z}$. The standardized weights from this regression are represented by $\boldsymbol{\Lambda}^*$ and are calculated as follows:

$$\boldsymbol{\Lambda}^* = \boldsymbol{Q}\boldsymbol{\Delta}\boldsymbol{Q}'.$$

Using these standardized weights, the vector of relative weights can be calculated:

$$\boldsymbol{\varepsilon} = \boldsymbol{\Lambda}^{*^{[2]}}\boldsymbol{\beta}^{*^{[2]}},$$

where $\boldsymbol{\Lambda}^{*^{[2]}} = ||\lambda_{ki}^{*2}||$ and $\boldsymbol{\beta}^{*^{[2]}} = ||\boldsymbol{\beta}_i^{*2}||$. Each λ_{ki}^{*2} represents the proportion of variance in $\boldsymbol{z}_i$ accounted for by $\boldsymbol{x}_i$. The values in $\boldsymbol{\varepsilon}$ should sum to R^2. However, if there are suppression effects, the total may exceed R^2 (Nathans et al., 2012). Dividing $\boldsymbol{\varepsilon}_p$ by R^2 gives a measure of how much variance predicted by the optimal model is attributable to predictor p. When predictors are uncorrelated, then $\boldsymbol{\varepsilon}$ contains the squared standardized regression coefficients.

From a computing perspective relative weights are easy to compute when compared to dominance analysis (Johnson, 2000). Summing to R^2 allows for relative weights to be easily understood as a partition of the total variance accounted for by the model and have the added value of reducing the effects of multicollinearity. However, relative weights do not neutralize the issue of correlated predictors; weights generally contain both unique and shared variance (Nathans et al., 2012).

In 2014 Thomas, Zumbo, Kwan, & Schweitzer published a reanalysis of Johnson's methods. Thomas et al. points out that Johnson's approach assumes that the variance of each $\boldsymbol{z}_k$ (the columns of $\boldsymbol{Z}$) could be partitioned between the $\boldsymbol{x}_i$ (columns of $\boldsymbol{X}$) based on the squared correlations between the $\boldsymbol{x}_i$ and a given $\boldsymbol{z}_k$. Thomas et. al emphasized the fact that the columns of $\boldsymbol{X}$ are generally correlated with each other making it inappropriate to use squared simple correlations as a method of partitioning variance accounted for by these columns. The authors do mention however that despite these mathematical issues past articles (i.e. Johnson, 2000; LeBreton, Ployhart, et al. 2004) have found surprising levels of agreement between the results of general dominance and relative weights.

Thomas et al., provide two examples of where relative weights and dominance analysis diverge. One of the examples showed a difference in the estimates of the percent of explained variance accounted for by each predictor and the other examples showed an inversion of the 2nd and 3rd ranked predictors when comparing general dominance and relative weights. The objections presented in the paper based on the derivation of relative weights are certainly a valid criticism and one that should be concerning to those who are considering using relative weights. However, the demonstrations of how the results of dominance analysis and relative weights differ in practice may leave some readers unconvinced that using relative weights would be problematic in practice, especially given the amount of computing power required to run dominance analyses.

2.2.8 Agreement Between Measures of Relative Importance

A summary of the approaches to relative importance analysis discussed in this paper is provided in Table 1. LeBreton et al. (2004) performed a Monte Carlo simulation that examined the agreement of relative importance methodologies. The study used the rankings produced by dominance analysis and calculated a Kendall's τ for the agreement of these rankings, with rankings based on squared zero-order correlations, squared beta coefficients, the Pratt measure, and relative weights analysis. The correlations ranged from .78 (squared beta) to .96 (relative weights), indicating a high, although not perfect, level of agreement. However, this study failed to provide a full correlation matrix for the relative importance measures and only dominance analysis was correlated with all alternative methods examined. The question regarding agreement amongst the other metrics still remained.

Despite the attention paid to methods of interpreting relative importance in regression, it is still common for published research to look to beta weights to determine the importance of variables used in regression analysis. To understand the meaning of beta weights, it is necessary to examine past work on regression weights.

2.3 Regression Weights

Optimal weights are produced by OLS regression. Optimal weights can be standardized or unstandardized. Standardized weights can be obtained by converting the scores on all variables in the model to z-scores. Unstandardized weights remain in the original variable metric. It is common for optimal weights to be reported in published research that employs OLS regression. Optimal weights are designed to minimize SSE and are a function of observed data (Davis-Stober, 2011). By prioritizing minimizing SSE in a particular sample, optimal weights capitalize on sample characteristics that may not be representative of the larger population and have occurred due to sampling error (Bobko, Roth, & Buster, 2007). Because optimal weights capitalize on chance sample characteristics, they can have issues in cross-validation when optimal weights from one sample are applied to a new sample. The new sample will not have all the characteristics that the initial regression model was designed to explain.

Equal weights have been examined as one alternative to optimal weights. Equal weights fall under the category of "improper linear models" discussed by Dawes (1979) and are often referred to as unit weights (Bobko et al. 2007). When equal weights are employed, the score on each predictor is converted to a z-score and each predictor is given an equal weight in the regression model. Unlike optimal weights, unit weights do not capitalize on sampling error, are not sensitive to outliers, violations of normality in the sample do not affect their performance in cross-validation, and they can perform similarly or better than optimal weights in cross-validation (Raju, Bilgic, Edwards, & Fleer, 1999; Wainer, 1976).

Wainer (1976) declared, "It don't make no nevermind" in reference to estimating weights in linear regression, he later corrected this to "It hardly makes no nevermind" (Wainer, 1978, p. 269). Wainer demonstrated that in some instances loss of variance explained when using equal weights (and removing variables with very small regression weights) as opposed to optimal weights is small, even when true population weights can be known. This loss of variance is even smaller when predictors are correlated, which is often the case in I/O. Ree et al. (1998) focus on how equal weighting schemes affect rankings. In I/O psychology there are many situations where ranking individuals is the goal, as opposed to providing a point estimate on the outcome variable of interest. For example, in selection the goal is usually to predict who will be the best rather than who will obtain a certain score on a performance review. Ree et al. found that a variety of weighting schemes would produce near-identical selection decisions based on ranking applicants.

It is important to note that, classically, the performance of regression weights in cross-validation has been evaluated in terms of the weights' ability to predict values in the outcome variable. This value is common in I/O psychology (and other applied areas), where the focus tends to be on the predictive validity of a system. However, weights can also be evaluated in terms of how well they perform in predicting the true population weight values. Davis-Stober (2011) chose to examine the performance of various fixed weighting schemes in terms of estimating population weight values, and found that standardized OLS weights outperform fixed weights (in regards to the Mean Squared Error) when the multiple R is equal to 0.6 and sample size is as low as 20. When the multiple R decreases, the sample size required for OLS weights to outperform fixed weights increases.

When it comes to weights, it is imperative that regression users have clear goals. It can be tempting to draw broad conclusions from optimal weights but the actual implications of optimal weights are very specific, perhaps more than many users realize. When the goal of a study is to influence practice, then presenting optimal weights without clear explanation of the implications may be misleading and even damaging.

2.3.1 Fungible Weights

Relative importance analyses such as dominance analysis and relative weights analysis have worked towards comparing the relative importance of predictors in a regression model (Johnson & Lebreton, 2004). However, these methods do not result in a measure of the overall model sensitivity. A measure of regression model sensitivity is absent from the literature and would allow a more complete understanding of regression analysis. Understanding methods we employ will allow us to reach more valid conclusions. Waller (2008) demonstrated that it was possible to generate infinite vectors of alternative weights in regression models with three or more predictors by reducing the R^2 value obtained by using optimal weights in OLS regression.

Waller (2008) uses the following procedure to produce alternative weight vectors. Once again, $\boldsymbol{X}$ is an $n \times p$ matrix, where n is the number of observations and p is the number of predictors. $\boldsymbol{R_X}$ is the predictor correlation matrix, $\boldsymbol{a}$ is the set of alternative standardized weights, and $\boldsymbol{\beta}$ is the set of optimal beta weights.

$$\hat{\boldsymbol{y}}_{\boldsymbol{\beta}} = \boldsymbol{X}\boldsymbol{\beta}.$$

$$\hat{\boldsymbol{y}}_{\boldsymbol{a}} = \boldsymbol{X}\boldsymbol{a}.$$

The correlation between the predicted criterion scores produced by the alternative and optimal weights is calculated as follows:

$$r_{\hat{\boldsymbol{y}}_a \hat{\boldsymbol{y}}_\beta} = \frac{\boldsymbol{a}'\boldsymbol{R_X}\boldsymbol{\beta}}{(\boldsymbol{a}'\boldsymbol{R_X}\boldsymbol{a})^{1/2}(\boldsymbol{\beta}'\boldsymbol{R_X}\boldsymbol{\beta})^{1/2}}. \tag{1}$$

Equation 1 can be reduced to an inner product of vectors $\boldsymbol{u}$ and $\boldsymbol{k}$, where both vectors are unit length:

$$r_{\hat{\boldsymbol{y}}_a \hat{\boldsymbol{y}}_\beta} = \boldsymbol{k}'\boldsymbol{u}. \tag{2}$$

Converting Equation 1 to Equation 2 is done by allowing $\boldsymbol{R_X}$ to be decomposed into a product of $\boldsymbol{V}$ and $\boldsymbol{\Lambda}$, where $\boldsymbol{V}$ is a $p \times p$ matrix of orthonormal eigenvectors and $\boldsymbol{\Lambda}$ is a diagonal $p \times p$ matrix containing the associated eigenvalues. Thus:

$$\boldsymbol{R_X} = \boldsymbol{V\Lambda V}'. \tag{3}$$

Values of $\boldsymbol{u}$ and $\boldsymbol{k}$ can be calculated as follows:

$$\boldsymbol{u} = \frac{\boldsymbol{\Lambda}^{1/2}\boldsymbol{V}'\boldsymbol{\beta}}{(\boldsymbol{\beta}'\boldsymbol{R_X}\boldsymbol{\beta})^{1/2}}.$$

$$\boldsymbol{k} = \frac{\boldsymbol{\Lambda}^{1/2}\boldsymbol{V}'\boldsymbol{a}}{(\boldsymbol{a}'\boldsymbol{R_X}\boldsymbol{a})^{1/2}}.$$

Now, given any $\boldsymbol{u}$ it is possible to find a corresponding $\boldsymbol{k}$. Allow for the following:

$$\boldsymbol{k} = r_{\hat{\boldsymbol{y}}_a\hat{\boldsymbol{y}}_{\boldsymbol{\beta}}}\boldsymbol{u} + \boldsymbol{Uz}(1 - r^2_{\hat{\boldsymbol{y}}_a\hat{\boldsymbol{y}}_{\boldsymbol{\beta}}})^{1/2},$$

where $\boldsymbol{U}$ is a $p \times (p-1)$ orthonormal matrix such that $\boldsymbol{U}'\boldsymbol{u} = \boldsymbol{0}$ and $\boldsymbol{z}$ is a $(p-1) \times p$ normalized random vector where $\boldsymbol{z}'\boldsymbol{z} = \boldsymbol{1}$. In the approach laid out in Waller (2008), $\boldsymbol{U}$ is constructed using the Gram-Schmidt method. Given these conditions it follows that,

$$\boldsymbol{k}'\boldsymbol{u} = r_{\hat{\boldsymbol{y}}_a\hat{\boldsymbol{y}}_{\boldsymbol{\beta}}} = (r_{\hat{\boldsymbol{y}}_a\hat{\boldsymbol{y}}_{\boldsymbol{\beta}}}\boldsymbol{u}' + (1 - r^2_{\hat{\boldsymbol{y}}_a\hat{\boldsymbol{y}}_{\boldsymbol{\beta}}})^{1/2}\boldsymbol{z}'\boldsymbol{U}')\boldsymbol{u}.$$

Remembering that $\boldsymbol{U}'\boldsymbol{u} = \boldsymbol{0}$ it is easy to see that an infinite number of $\boldsymbol{z}$ can be constructed. Given this infinite number of $\boldsymbol{z}$ an infinite number of $\boldsymbol{k}$ can also be constructed. At this point let $\boldsymbol{k}_i$ $(i = 1, 2, \ldots, \infty)$ refer to the i^{th} vector in the infinite set. Given a value of $\boldsymbol{k}_i$ the goal is to find the corresponding $\boldsymbol{a}_i$.

Let s be a constant and,

$$\tilde{\boldsymbol{a}}_i = \frac{\boldsymbol{a}_i}{s} = \boldsymbol{V}\boldsymbol{\Lambda}^{-1/2}\boldsymbol{k}_i. \tag{4}$$

The right hand side of this equation scales and rotates $\boldsymbol{k}_i$ so that it aligns with $\boldsymbol{a}_i$. It is still necessary to find an s that will scale $\tilde{\boldsymbol{a}}_i$ to minimize the SSE_a. Allow s to be:

$$s = \frac{\boldsymbol{r}'_{xy}\tilde{\boldsymbol{a}}_i}{\tilde{\boldsymbol{a}}'_i\boldsymbol{R}_{\boldsymbol{X}}\tilde{\boldsymbol{a}}_i}.$$

Keeping in mind (3) and (4) $\boldsymbol{a}_i$ can b expressed as,

$$\boldsymbol{a}_i = (\boldsymbol{r}'_{xy}\boldsymbol{V}\boldsymbol{\Lambda}^{1/2}\boldsymbol{k})\boldsymbol{V}\boldsymbol{\Lambda}^{-1/2}\boldsymbol{k}.$$

Each $\boldsymbol{a}_i$ will satisfy the following:

$$R^2_{\boldsymbol{a}_i} = r^2_{\boldsymbol{y}\hat{\boldsymbol{y}}_a} = \boldsymbol{a}'_i\boldsymbol{R}_{\boldsymbol{X}}\boldsymbol{a}_i.$$

This is a quadratic form that defines a hyper-ellipsoid in p-dimensional space (Jones, 2013; Waller, 2008). The fungible weight vectors for a given $\boldsymbol{R}^2_{\boldsymbol{a}}$ lie at the intersection of this hyper-ellipsoid with a $p-1$ dimensional hyper-plane defined by:

$$r_{\hat{\boldsymbol{y}}_a\hat{\boldsymbol{y}}_b}r_{\boldsymbol{y}\hat{\boldsymbol{y}}_a}r_{\boldsymbol{y}\hat{\boldsymbol{y}}_b} = \boldsymbol{a}'\boldsymbol{R}_{\boldsymbol{X}}\boldsymbol{b}.$$

Waller (2008) used the fungible weights approach to re-examine findings presented by Kuncel, Hezlett, and Ones (2001) concerning the relationship between

GRE scores and graduate school performance. Waller generated 20,000 alternative weight vectors by reducing the R^2 from the initial study by 0.005, and demonstrated that there is a large amount of variability in the value of the standardized regression weights associated with each predictor.

This process differs from measures of relative importance because it keeps the sample characteristics and variables in the model the same, and only changes the value of R^2. It also does not focus on producing a rank order of relative importance among variables, but rather a measure of overall model sensitivity. Waller states that relative importance is difficult to determine given the presence of fungible weights. When thinking about the relative importance metrics reviewed above the Pratt measure immediately comes to mind as one metric that would be particular hard to interpret for models that are insensitive to weight variations. For every vector of alternative weights you could calculate a corresponding vector of Pratt measures, calling into question the value of the initial metric.

Four factors affect the results of the fungible weights analysis presented in Waller (2008): the model R^2, the eigen structure of the correlation matrix of the predictors, the orientation of the vector of beta weights with respect to structure of the predictor correlation matrix, and the number of predictors in the model (Jones, 2013). It is important to highlight that sample size is not a factor in fungible weights analysis and, therefore, is markedly different from other techniques that choose to focus on sampling variability. The model R^2 and the number of predictors are particularly interesting when thinking about an appropriate comparison group for a model. Depending on the field of study, different sizes of model R^2 are considered interesting. It is interesting to investigate a model's sensitivity in isolation and also compare the model sensitivity to other, similar models.

The current study examined how published literature performs when subjected to fungible weights analysis. The study also examined how published models perform when compared to similar, simulated regression models.

2.4 Current Study

This dissertation examined how regression analysis has been used in the I/O psychology literature, as well as the sensitivity of those regression models and the level of agreement of relative importance indices when applied to regression models within the literature. Published literature was reviewed, coded, and re-analyzed using existing and new approaches for multiple regression interpretation. The research focused on what topics have been studied using regression and what types of conclusions have been drawn from OLS regression analyses. The research also examined how often and what relative importance analyses are employed to draw conclusions regarding the importance of predictors.

The study also examined the sensitivity and variability of weights in the published I/O literature using fungible weights and predicted performance of equal weights. This study indicates how current practices in reporting of regression results may be misleading to consumers of published I/O research. The results of this study hopefully will encourage members of the I/O community to carefully evaluate current approaches to regression interpretation. Research and practice can benefit from a deeper understand of regression analysis.

3 Methods

3.1 Database of Past Literature

To determine how the use of multiple regression weights has impacted industrial organizational psychology, published articles that have been distributed to a wide audience were the focus of this review. Articles published in the years 2003 through 2014 in the *Journal of Applied Psychology* (JAP), and alternating years of *Psychological Science* and *Academy of Management Journal* (AMJ) (specifically 2003, 2005, 2007, 2009, 2011, and 2013 *Psychological Science* and 2004, 2006, 2008, 2010, 2012, and 2014 in AMJ), three popular top-tier, peer-reviewed journals in work and general psychology, and prime resources for I/O psychologists, human resource management practitioners, and people from across the field of psychology were reviewed. This timeframe was chosen to allow enough time after Johnson (2000) for authors to have access to relative weights analysis as well as various other methods for interpreting the relative importance of predictors in a regression model.

To be included in the study analysis, an article must have included an OLS regression with three or more predictor variables and not included interaction or exponent terms. These inclusion criteria were based on the requirements necessary to put the regression equations through further analysis. In order to produce an infinite amount of alternative weight vectors, fungible weights analysis requires three or more predictor variables. Both fungible weights and relative importance metrics require a correlation matrix. Correlations for interactions and exponent terms are generally not provided in the published literature and therefore this study focused on regression analyses that would be eligible for further analyses if predictor and criterion correlation matrices were provided. It was necessary for regression coefficients, or the results of one of the relative importance analyses reviewed above, to be shown somewhere (either in the text or a table) in the article or one of its published appendices. As a result of the aforementioned inclusion criterion, articles where regression procedures were referenced but results were not displayed were excluded from this study. Articles that used hierarchical multiple regression were analyzed, but only the most inclusive model in the hierarchical analysis was examined. To be used in further analysis, an article must have included a full correlation matrix of all the variables included in the regression so that the necessary analyses could be run. Overall, 197 articles were found that met the inclusion criteria to be included in the database of past literature and 117 of those articles contained a full predictor and criterion correlation matrix and were eligible to be included in further analyses. Of the 80 articles that did not contain a full correlation matrix, 4 (5.00%) had at least some intercorrelations for all variables, 54 (67.50%) were missing at least one entire variable's correlations, and 22 (27.50%) did not provide any correlation table. It was concerning to find so many articles that were lacking a full predictor and criterion correlation matrix. Not only are correlation matrices useful for interpreting findings within a given study, correlation matrices are essential for scientists attempting to conduct meta analyses. Missing correlations can harm current readers as well as negatively impact the accuracy of future meta-analytic findings.

Each article was coded to determine how the regression results were interpreted and to examine the impact of the article. To quantify the impact of the article the number of times the article had been cited, according to Google Scholar, was recorded on February 24, 2017. The articles' authors' country affiliations were recorded to track how widespread the use of regression is and to determine how representative the sample is of widespread practices. The number of predictors was also recorded. The topic of the regression was coded according to the broad topic areas identified by Cascio and Aguinis (2008) in their content analysis of articles published in JAP and Personnel Psychology. These topics were: job analysis, research methodology and psychometric issues, predictors of performance, performance measurement and work outcomes, training and development, industrial relations, reward systems, work motivation and job attitudes, leader influences, work groups and teams, career issues, decision making, human factors and applied experimental psychology, consumer behaviors, and societal issues. Articles that did not fit into one of those categories were assigned a category of other and the topic was noted. After all articles were coded the other category was reviewed and new categories were created. It also was noted whether or not the regression was conducted on primary or meta-analytic data, and the sample size used in the regression. The articles were examined to determine what conclusions were drawn from the regressions, specifically whether or not a statement was made to indicate the relative importance of variables based on the regression. The articles were also coded for whether a relative importance analysis was conducted, and if so, what method was used.

Of the $\boldsymbol{R_X}$ in the database, 98.28% of the matrices were positive definite, meaning that one or more of the eigen values for $\boldsymbol{R_X}$ was not positive. The condition number, κ, was calculated for each positive definite $\boldsymbol{R_X}$. Where κ is calculated as:

$$\kappa = \sqrt{\frac{\lambda_1}{\lambda_p}}.$$

Where λ_1 is the largest eigen value for $\boldsymbol{R_X}$ and λ_p is the smallest eigen value for $\boldsymbol{R_X}$ (Cohen, Cohen, West, & Aiken, 2003). κ is a popular measure of multicollinearity and is also related to the shape of the ellipsoid in fungible weights (Jones, 2013). When the eigen values of $\boldsymbol{R_X}$ are close to equal, the ellipsoid will be close to spherical. When there is a large difference in the sizes of the eigen values for $\boldsymbol{R_X}$ the ellipsoid (or in the case of more than 3 dimensions, hyper ellipsoid) will be (hyper) cigar or (hyper) pancake shaped (Jones, 2013; Waller & Jones, 2009).

3.2 Analysis

3.2.1 Database Summary

Descriptive statistics were used to describe the articles in the database. The mean and standard deviation were calculated for number of times an article has been cited and number of predictors used in each regression. Frequencies were calculated for topic of regression analysis, meta-analysis vs. primary data, type of conclusion drawn from the regression analysis, and number of articles that used regression without providing a complete correlation matrix. A description of all data collected throughout this dissertation is provided in Table 2.

3.2.2 Relative Importance Analysis

Relative importance analyses were conducted for all regressions that met the inclusion criteria for the literature review and also contained a correlation matrix of all variables included in the regression. For meta analyses, when available, corrected correlations were used. The relative importance analyses were conducted using an edited version of the yhat package in R (Nimon & Roberts, 2012). Specifically, the calc.yhat function was edited to remove excess calculations for the sake of computational efficiency. The program was run to obtain a matrix of the beta weights, zero-order correlation coefficients, squared structure coefficients, unique coefficients from commonality analysis, the sum of common coefficients from commonality analysis, general dominance weights, Pratt measures, and relative weights.

For each regression, an intraclass correlation was calculated to determine the level of agreement between the rank of the predictors produced by the various relative importance measures. For articles that drew conclusions based on the rank ordering or relative size of beta weights, it will be determined which relative importance analyses support or refute the conclusion in the article. A correlation table of Kendall's taus also was also calculated for these measures for each regression. These correlation tables allowed the mean and standard deviation for Kendall's tau to be computed across all regressions for each pair of relative importance analyses. These correlations demonstrated which procedures showed the highest levels of agreement in the given sample.

3.2.3 Sensitivity Analysis

For those articles that met the inclusion criteria for the literature review as well as contained a correlation matrix for all variables included in the regression further analyses were run to examine the sensitivity of those models. To critically examine the use of multiple regression weights within the I/O literature, the fungible weights methods described in Waller (2008) were used. Correlation matrices from the articles were manipulated to generate fungible weights using the R-code presented in the original article. Fungible weights were generated for an R^2 value that was 0.01 less than that produced by the optimal weights. This analysis produced 5,000 vectors of alternative standardized weights. The output included the minimum, maximum, mean, and median value of the alternative weights associated with each predictor variable.

Additional code was added to examine how many of these 5,000 vectors contain a change in the rank order of the variables compared to the rank order associated with the original β_i. To further examine sensitivity, Kendall's τ was calculated to determine the level of agreement between the rank ordering of the beta weights associated with the IVs in the optimal solution and the rank ordering of the beta weights associated with the IVs in the 5,000 alternative solutions. The average, minimum, and maximum Kendall's τ across all alternative weight vectors was included in the output.

Waller (2008) suggested that one possible measure of model sensitivity would be the cosine between $\boldsymbol{k}_i$ and $\boldsymbol{k}_j$, where the angle between $\boldsymbol{k}_i$ and $\boldsymbol{k}_j$ is twice the angle between a given $\boldsymbol{k}_i$ and $\boldsymbol{u}$. Recall that $\boldsymbol{u}$ and all values of $\boldsymbol{k}$ are unit vectors defined in the fungible weights section earlier. Allowing O to be the origin of an 3-dimensional Cartesian coordinate system, this cosine can be calculated as:

$$cos\measuredangle\boldsymbol{k}_iO\boldsymbol{k}_j = 2r^2_{\hat{y_a}\hat{y_b}} - 1$$

The cosine may not be as intuitive a metric as some might hope. As a reminder, when thinking about a unit circle, the cosine is 1 when the angle is 0°, the cosine is 0 when the angle is 90°, and the cosine continues to move from 0 to -1 as the angle moves from 90° to 180°. This means that as the cosine value approaches 1 the angle is smaller, the closer it gets to -1, the larger the angle. The idea is that the smaller the angle, the more similar the alternative weight vectors will be to each other, while larger angles will be associated with more dissimilar weights. For each regression the $cos\measuredangle\boldsymbol{k}_iO\boldsymbol{k}_j$ was calculated and the meaning of this metric was examined.

This paper also examined whether regressions where equal weights result in a similar R^2 value to the R^2 produced by optimal weights were less sensitive to weighting changes. In order to investigate equal weights and model sensitivity each regression that was put through the fungible weights analysis was also examined to determine the R^2 for a model using unit weights. Unit weights were assigned as follows: -1 was assigned to predictors with a negative correlation with the criterion and 1 was assigned to predictors with a positive correlation with the criterion. R^2 was calculated according to the methods laid out in Dana and Dawes (2004). Specifically, let $\boldsymbol{\beta}_U$ be the vector of unit weights, $\boldsymbol{R_x}$ is the predictor correlation matrix, and $\boldsymbol{r_{yX}}$ be the vector of correlations between the predictor variables and the criterion. The R^2 of the unit weighted vector was calculated as follows:

$$R_U^2 = \frac{(\boldsymbol{\beta}_U' \boldsymbol{r_{yX}})^2}{\boldsymbol{\beta}_U' \boldsymbol{R}_x \boldsymbol{\beta}_U}.$$

3.2.4 Simulation Study

Using fungible weights to re-examine past findings provided information on the range of outcomes found in the published literature. However, the results from published literature are still a relatively small set of possibilities and do not provide insight into how a particular model performs when compared to similar models. Although the average Kendall's τ can be examined in the context of existing knowledge about correlations it is unclear what might be considered a "good" value. To determine what could be considered a high vs. low value for the average Kendall's τ, a simulation was run.

Five regression equations from the published literature were selected. The top 3 most highly cited articles that drew conclusions based on the size of the beta weights and contained full correlation matrices were chosen. The top 2 most highly cited articles that conducted at least one relative importance analysis and contained full, positive definite, correlation matrices were also chosen. Given that articles that drew conclusions based on the beta weights or conducted relative importance analyses indicate that the author's were interested in making statements about the relative size or importance of predictors, it is fascinating to take a deeper dive and examine these articles under a new lens. For each of these regressions 1000 correlation matrices were produced using the fungibleR function provided in Waller (2016). This function was used to produce positive definite predictor correlation matrices, denoted $\boldsymbol{R}^*_{\boldsymbol{X}}$, which satisfied the following equation:

$$\boldsymbol{\beta}^T \boldsymbol{R}^*_{\boldsymbol{X}} \boldsymbol{\beta} = R^2.$$

Where $\boldsymbol{\beta}$ is the vector of standardized OLS regression weights and R^2 is the model R^2. These correlation matrices were then put through the fungible weights analysis, where 5000 alternative weight vectors were produced for each $\boldsymbol{R}^*_{\boldsymbol{X}}$. The average Kendall's τ's were used to create an empirical distribution. Since the fungible weights analysis used in this study examined a sample of 5000 alternative weight vectors from drawn an infinite number of possible alternative weight vectors, it was important to also examine the variability of this procedure when trying to compare results from different models. In order to create a sensible comparison for the distribution created from the 1000 $\boldsymbol{R}^*_{\boldsymbol{X}}$, another distribution was created by running fungible weights using the original $\boldsymbol{R}_{\boldsymbol{X}}$ 1000 times.

Comparing the two distributions demonstrated how the model with the original $\boldsymbol{R}_{\boldsymbol{X}}$ performed compared to other $\boldsymbol{R}^*_{\boldsymbol{X}}$ while holding the OLS model R^2 and $\boldsymbol{\beta}$ constant. It is a highly constrained simulation that provides one possible method for evaluating the results of fungible weights.

4 Results

4.1 Database Summary

After reviewing the relevant journals over the given years 197 articles were found that met the inclusion criteria for the literature review, a full list of articles included in the literature review can be found in Appendix A, with a summary of the article characteristics found in Table 3. The articles were authored by people from institutions in 23 different countries, indicating the international representation in this review. On average articles had authors associated with 1.28 countries. This indicates that regression is a technique used by scholars around the globe, including when scholars residing in different countries collaborate with one another. A full list of countries and number of articles authored by people associated with those countries can be found in Table 4. The overwhelming majority of articles (84.26%) had at least one author associated with the US. A breakdown of the number of articles per topic area is provided in Table 5. Most articles were able to be coded into the categories provided by Cascio and Aguinis (2008). Additional categories were added for developmental psychology, adult psychology, clinical interventions, health psychology, neuropsychology, and psychopathology. Khaire and Wadhwani (2010) wrote about constructing meaning and value in the emerging market of modern indian art, this article defied classification and was classified as “other”. The most common categories for articles to fall into were predictors of performance (25.38%), work motivation and attitudes (20.30%), work groups-teams (15.23%), and leader influences (10.66%). The distribution across categories is not surprising given that work in these areas often rely on regression and the distribution reflects some of the findings for more recent years presented in Cascio and Aguinis (2008). For a breakdown of articles by topic area for only those articles published in JAP or AMJ see

Table 6.

The number of times each article was cited according to the Google Scholar database was retrieved and recorded on February 24, 2017. The purpose of recording the number of citations was to get a measure of impact of the articles included in the review and further analysis. A histogram of the number of times the articles included in the database summary were cited is provided in Figure 1. On average articles were cited 223 times, though the distribution was positively skewed with a median of 108 and a standard deviation of 328.79. This indicates that the findings from regression analyses are influential, with the findings from these articles going on to influence the work of many others. Figure 2 shows a distogram of the number of times only the meta-analysis articles were cited.

Of the 197 articles, 80 (40.61%) of them did not contain a full correlation matrix for the predictor and criterion variables used in the regression. The lack of complete correlation matrices was surprising given that bivariate correlations can be very useful when making an effort to interpret larger models.

Fifteen articles (7.61%) drew conclusions based on the size of the predictor weights in at least one of their regression equations. These conclusions included discussing the magnitude of the betas, comparing the beta sizes to one another and pointing out which was larger, and declaring that the predictor with the largest associated beta coefficient was the optimal predictor. For example, Bartram (2005) used beta weights to rank the importance of predictors in predicting overall job performance (OJP) stating, "Of the eight competency ratings, those most strongly related to OJP ratings, in order of importance ... are Analyzing & Interpreting, Organizing & Executing, Enterprising & Performing, Leading & Deciding, and Creating & Conceptualizing. The more contextual competencies (Supporting & Cooperating, Adapt- ing & Coping, Interacting & Presenting) are less strongly related" (p.

1196). Ford, Heinen, and Langkamer (2007) simply pointed out the largest weight, "The largest beta weights were found for family conflict and family stress" (p. 64). Both of these articles failed to provide complete correlation matrices in the article and therefore were not included in further analysis.

Nine articles (4.6%) conducted some form of relative importance analysis, only one of these articles was one of the 15 articles mentioned above that drew conclusions based on the size of the beta weights. Six articles used relative weights, 2 used dominance analysis, and an additional article used both relative weights and dominance analysis. Out of the articles that made a point of mentioning beta size, 4 included a full correlation matrix which allowed the regressions to be put through further analyses. Seventy six (38.58%) articles mentioned and/or interpreted the model R^2 when discussing regression results. One hundred seventy three (87.82%) articles interpreted the significance of individual beta weights and 126 articles (63.96%) interpreted the sign associated with the weight. Sixty articles (30.46%) published an adjusted R^2 metric, although only one article, Van Iddekinge, Putka, and Campbell (2011), stated what kind of correction was used. For those interested, adjusted R^2 were calculated using Wherry's (1931) correction for all regressions that had an associated sample size and a complete positive definite correlation matrix, summary metrics regarding these adjusted R^2, as well as summary metrics regarding other findings from the analyses in this paper, can be found in Table 13. Wherry's (1931) correction was chosen for these calculations since it is the default correction used in SPSS, a popular software package for statistical analysis.

Of the articles included in the database summary, 117 contained full correlation matrices for the regressions that fit our inclusion criteria. From these 117 articles, correlation matrices from 409 separate regressions were entered into the dataset to be put through further analyses. The number of predictors in the individual regressions ranged from 3 to 25, with a mean of 6.97, median of 6 and standard deviation of 3.92. The full distribution of the number of predictors can be seen in Figure 4. Of these 409 regression 7 were unable to be analyzed due to a lack of a positive definite correlation matrix. None of these non-positive definite correlation matrices came from meta analyses. The articles lacking a positive definite correlation matrix are noted in Appendix A. Matrices that were flagged as not positive definite were double checked with the source material to ensure that the tables were entered correctly. At this point it is important to note that these matrices may have ended up being not positive definite due to typos in the published materials. After removing the non-positive definite $\boldsymbol{R_X}$, 402 regressions from the database summary were able to be put through further analyses. κ was calculated for each of the positive definite $\boldsymbol{R_X}$. κ from 1.11 to 11.29 with a mean of 2.73 and a standard deviation of 1.27. The full distribution of κ can be seen in Figure 3.

4.2 Relative Importance Analysis

For each of the 402 regressions with a positive definite $\boldsymbol{R_X}$, Kendall's τ was calculated between the rank order of the magnitude of each of the relative importance indices studied (for a full list of regressions and the associated Kendall's τ see Appendix D). The Kendall's τ were calculated between the rank of the standardized OLS regression weights (β_i), the bivariate correlations between the predictors and the criterion ($r_{\boldsymbol{yx}_i}$), the general dominance weights (GD), the relative weights ($\boldsymbol{\varepsilon}_i$), the squared structure coefficients ($r^2_{S_i}$), the unique effects from commonality analysis (U), the common effects from commonality analysis (C), and the Pratt measure (m_i). The averages and standard deviations for these Kendall's τ can be seen in

Table 7. An intraclass correlation was also calculated to measure the overall agreement between the ranks produced by all the relative importance indices. A full distribution of the intraclass correlations across the 402 regressions can be seen in Figure 5. The ICC tended to be quite high with a mean of 0.81, with a first quartile of 0.73 and third quartile of 0.91. Ciccheti (1994) stated that ICC values ranging from 0.6 to 0.74 are considered good with ICC values at or above 0.75 considered excellent, the majority of the ICCs in this study fall into the excellent range. The level of agreement is not surprising given that some of these metrics tap into the same measurements and others are meant as approximations of each other, such as with general dominance and relative weights.

The more interesting details come from examining the average Kendall's τ between various pairs of metrics. The average Kendall's τ's ranged from 0.41 (between beta weights and common effects from commonality analysis) to near perfect. Unsurprisingly the average correlation between structure coefficients and zero-order correlations was close to perfect (rounding to the second decimal place left it at 1.00) with almost no variation across regressions. Given that the structure coefficient is the correlation between the predictor score and the estimated criterion value the agreement of the ranking of this metric and the the ranking of the zero order correlations is to be expected. The next-highest level of agreement was found between relative weights and general dominance weights which had an average correlation of 0.97 with a standard deviation of only 0.07. Given that these two metrics are meant to be on the same scale the question might also arise about the absolute level of agreement between the outputs. In order to look at the absolute agreement, the relative weights and general dominance weights associated with each predictor in each model were examined. Across all 2803 variables that had associated relative weights and general dominance weights the average difference between these two metrics was 0.000001 with a standard deviation of 0.003. Given that the averages of general dominance weights and relative weights in this study was 0.041, 0.000001 is a small difference. This indicates that despite the theoretical differences in the derivations of these two metrics, within this sample relative weights is doing quite well at providing similar rankings to general dominance analysis and is doing a decent job at approximating the precise output as well. It is important to emphasize that these findings are sample specific and do not indicate that relative weights and general dominance will always produce findings with high agreement.

Some people might be interested in simply identifying the single "most important" predictor in a model. So, how did the eight metrics examined do in regards to agreeing on the top ranked predictor in a model? Of the regressions examined, 112 (27.86%) of them had agreement across all 8 indices on which predictor was the most important, emphasizing that the various importance metrics are measuring different constructs. The median number of metrics that agreed on which variable was the most important in this sample was 6. To see a full distribution of how many metrics agreed on the top ranked predictor see Figure **6**.

There were only 4 articles that drew conclusions based on the size of the betas and had full correlation tables. All four articles were looked at individually to determine which relative importance indices would agree or disagree with the conclusions drawn in the articles. The values of the relative importance indices in this paper may differ slightly from those in the published articles. The relative importance values in the tables in this paper are based on calculations done using the published correlation coefficients and therefore may differ slightly based on rounding or other errors in the publications.

Mumford, Van Iddekinge, Morgeson, and Campion (2008) which focused on the development and validity of a situational judgement test (SJT) for team role knowledge called the Team Role Test (TRT). The article had been cited 102 times as of February 24, 2017. In regards to the regressions run in the article the authors found "The TRT emerged as the strongest predictor of task and overall role performance (βs=.35 and .30, respectively), whereas agreeableness was the best predictor of social role performance (β=.28)" (p. 259). Let's examine the regressions predicting task role performance from mental ability, agreeableness, conscientiousness, emotional stability, extraversion, openness, and overall TRT scores more carefully. In Table 8 you will see the raw scores and ranks across the relative importance indices examined in this study. All importance indices agree with Mumford et al.'s conclusion that TRT is the strongest predictor of task performance. All indices except commonality coefficients ranked emotional stability as the second most "important". As lower ranked variables are examined, agreement between metrics becomes less consistent, but none of the metrics disagree with the statement that TRT is the strongest predictor.

Next let's take a look at Klehe and Anderson (2007). The authors examined the difference in motivation and ability across typical performance and maximum performance . The article has been cited 68 times as of February 24, 2017. They found that "the best predictor of typical performance during both performance periods was direction (β=.44 and β=.42, respectively, both ps $<$ .01). The second most relevant predictor was the procedural skills used during the task (β=.21 and β=.25, respectively, both ps$<$ .01)" (p. 987). The regression of typical performance at time 2 on direction, persistence, computer self efficacy, task valence, and working smart (referred to as procedural skills in the text of the article) was examined. Results from the relative importance analyses can be seen in Table 9. Consistent with the authors' statement, all relative importance measures ranked Direction as the most important predictor in this regression equation. However, when it came to the second most important predictor conclusions differed with 4 (50%) of the metrics ranking working smart second, with the remaining four metrics evenly split between ranking computer self efficacy and task valence as the second most important predictor. If Klehe and Anderson had used first order correlations, squared structure coefficients, common effects, or the Pratt measure they would have drawn a different conclusion about which predictor was the second most relevant.

Dabos and Rousseau (2004) studied how mutuality and reciprocity in psychological contracts was related to performance outcomes. The authors used regression coefficients to make conclusions about their model. The article has been cited 516 times as of February 24, 2017. The regression of scientist's perception of director transactional obligations onto director perception of director transactional obligations, director perception of director relational obligations, and director perception of director balanced obligations was examined. They found that "when the scientist's perception of director transactional obligations was regressed onto all corresponding director scales, director transactional (D) was the strongest predictor (B=0.26, $p< .05$)." (p.62). Results from the relative importance analyses can be found in Table 10. The ranks across all indices agree, indicating that all approaches would confirm the conclusion in the article. This is not surprising given that there were few predictors in the model and a decent spread across the correlations between the predictor and criterion.

Gupta, Ganster, and Kepes (2013) developed a measure of sales self-efficacy and studied the incremental validity of this new measure above and beyond the Big 5 personality traits. The authors used regression coefficients and dominance analysis to draw conclusions. They found that "As expected, SSE was the largest predictor of sales performance (β = .28, p < .01) and PA (β =.16, p < .01) in the concurrent study" (p. 694). The article has been cited 11 times as of February 24, 2017. The regression of sales performance onto conscientiousness, extraversion, agreeableness, openness to experience, emotional stability, and total sales self-efficacy was examined. The results from the relative importance analyses can be found in Table 11. The ranks for the most important variable and the second most important variable agree across all measures.

4.3 Sensitivity Analysis

In addition to the regressions removed due to the lack of a positive definite correlation matrix, an additional 15 regressions could not be run through sensitivity analyses due to the fact that the model R^2 derived from the correlation matrix was less than 0.01. In these cases reducing the model R^2 by 0.01 resulted in a negative value for the alternative model R^2 . This meant that 387 regressions, rather than 402 regressions, were put through sensitivity analysis.

Only 15 (3.87%) regressions had all 5000 alternative weight vectors produce the same rank of the variables according to weight that was present in the OLS solution vector, 205 (52.97%) of the regressions had 1000 or less alternative weight vectors preserve the entire rank. A full distribution of the results across the 387 regressions of the number of vectors preserving this order (out of the 5000 alternative weight vectors produced for each regression) can be seen in Figure 7. When examining just the top ranked weight and whether or not that remained associated with the same variable across alternative weighting vectors, the results were more favorable. A total of 91 (23.51%) regressions had the OLS weight vector and all 5000 alternative weight vectors agreed on which variable was ranked as number one. None of the regressions had 1000 or less alternative weight vectors preserve the top ranked variable. A full distribution for the number of vectors (out of 5000) that preserved the top ranking can be seen in Figure 8. Some might be curious about how often the alternative vectors agreed with the initial $\boldsymbol{\beta}$ on which variable was associated with the lowest rank. A total of 153 (39.53%) regressions had the OLS weight vector and all 5000 alternative weight vectors agree on which variable was lowest ranking. A full distribution for the number of vectors (out of 5000) that preserved the lowest ranking can be seen in Figure 9.

Given that some studies focus on the rank in magnitude, rather than the rank in values, the agreement based on the absolute values of the original and alternative weight vectors was also examined. When looking at the absolute values of weights, only 6 (1.55%) regressions had all 5000 alternative weight vectors produce the same rank of the variables according to weight that was present in the OLS solution vector, 281 (72.61%) of the regressions had 1000 or less alternative weight vectors preserve the entire rank. A full distribution of the results across the 387 regressions of the number of vectors preserving this order (out of the 5000 alternative weight vectors produced for each regression) can be seen in Figure 10. When examining just the top ranked weight based on absolute value and whether or not that remained associated with the same variable across alternative weighting vectors, the results were slightly more favorable. A total of 17 (4.39%) regressions had the OLS weight vector and all 5000 alternative weight vectors agreed on which variable was ranked as number one. A total of 33 (8.53%) regressions had 1000 or less alternative weight vectors preserve the top ranked variable. A full distribution for the number of vectors (out of 5000) that preserved the top ranking can be seen in Figure 11. A total of 130 (33.59%) regressions had the OLS weight vector and all 5000 alternative weight vectors agree on which variable was lowest ranking. A full distribution for the number of vectors (out of 5000) that preserved the lowest ranking can be seen in Figure 12. Across the board, examining the rank order of the magnitudes resulted in more disagreement than examining rank order according to the raw values.

The rank ordering of alternative weight vectors may be examined when conclusions are drawn based on the values of the β_i. The fungible weights results from the four regressions analyzed in the relative importance analyses above were examined in regards to fungible weights. Mumford et al. (2008) used the β_i to identify the strongest predictor, and all relative importance analyses agreed that the TRT was the strongest predictor of task performance. However, only 61.40% of alternative weight vectors ranked TRT as the strongest predictor of task performance, and only 19.24% of alternative weight vectors preserved the entire rank order from the OLS weight vector. Klehe and Anderson (2007), used the β_i to identify the best predictor and second best predictor, all relative importance analyses agreed on the most important predictor and 50% agreed on the second most important predictor. In the fungible weights analysis, 87.74% of alternative weight vectors agreed with the OLS weight vector on which variable was ranked number one and 27.48% of alternative weight vectors preserved the entire rank order of the OLS weights. Dabos and Rousseau (2004) used the β_i to identify the strongest predictor, with all relative importance indices agreeing on the full rank order of predictors. This regression had high agreement in the fungible weights analysis as well with 93.66% of alternative weight vectors agreeing with the OLS weight vector on which variable was ranked number one and preserving the entire rank order of the OLS weights. The final regression from Gupta et al. (2013) used the β_i to identify the largest predictor and all of the relative importance analyses agreed on the largest and second largest predictor. In the fungible weights analysis, 89.08% of alternative weight vectors agreed with the OLS weight vector on which variable was ranked number one and 23.30% of alternative weight vectors preserved the entire rank order of the OLS weights. It is clear that fungible weights provides information that is not captured within relative importance analyses and can call into question the results of relative importance analyses.

In order to summarize the agreement of the rank order between the alternative weights vectors and the OLS weight vector the Kendall's τ between the rank order of the predictors according to the OLS weights and alternative weights was calculated for each alternative weight vector and averaged across the 5000 alternative vectors for each regression. The distribution of these average correlations can be seen in Figure 13. The distribution has a mean of 0.79 and a standard deviation of 0.14. It is important to note that the Kendall's τ is focused on the order preservation in alternative weight vectors. When using the absolute values of weights the agreement based on the metric also decreases. The distribution of these average correlations when absolute values of weights are used can be seen in Figure 14. Some might be interested in the distribution of the minimum Kendall's τ for each regression, which can demonstrate how dramatic rank disagreement can be for a given regression. Figure 15 shows the distribution for the minimum τ when using raw values of weights, and Figure 16 shows the distribution for the minimum τ when using absolute values of weights. Information on the distributions of the maximum, median, first quartile, and third quartile Kendall's τ can be found in Table 13. These correlations are interesting summary metrics to examine from the perspective of determining if different weight rank orders can result in a similar model fit index but it is not the same as measuring the variation in the alternative weights for a given predictor.

Waller (2008) suggests that one possible measure of model sensitivity would be $cos\measuredangle \boldsymbol{k}_i O \boldsymbol{k}_j$, to gain some insight into how this metric functions it makes sense to see how it relates to the the average τ discussed above. The correlation between the cosine and the average τ is 0.47. This makes sense- it would be expected that when a model is more sensitive to weight fluctuations, and therefore the alternative vectors are more similar so the angle between them is smaller and the cosine is larger, that there would be less rank shifts in the alternative weighting vectors. The full distribution for this cosine metric can be seen in Figure 17.

When looking at the formula for $cos\measuredangle \boldsymbol{k}_i O \boldsymbol{k}_j$, it is clear that this metric is dependent on the relationship between predicted values of y produced by the optimal and alternative weight vectors. The relationship between between these predicted y values is dependent upon the decrease in model fit between optimal and alternative models. In the current analysis the absolute value of the reduction of R^2 was kept constant, but this meant that the percent reduction of R^2 varied across models. The percent reduction ranged from 1.20% to 83.33%, with a mean of 6.93% and standard deviation of 8.89%. To see a full distribution of the percent reduction in R^2 between optimal and alternative models when reducing the optimal R^2 by 0.01 see Figure 18. The relationship between the percent reduction and $cos\measuredangle \boldsymbol{k}_i O \boldsymbol{k}_j$ is shown in Figure 19. Based on the equations covered earlier in this paper it is not surprising to see a linear relationship between $cos\measuredangle \boldsymbol{k}_i O \boldsymbol{k}_j$ and the percent reduction in R^2 between optimal and alternative weight models. In fact, as Waller (2008) notes, $cos\measuredangle \boldsymbol{k}_i O \boldsymbol{k}_j$ can be calculated as:

$$cos\measuredangle \boldsymbol{k}_i O \boldsymbol{k}_j = 2\frac{r^2_{y\hat{y_a}}}{r^2_{y\hat{y_b}}} - 1$$

Given the relationship between $cos\measuredangle \boldsymbol{k}_i O \boldsymbol{k}_j$ and the percent reduction in R^2, this brought up the question of what would happen if all the model R^2 were reduced by a constant percent instead of a constant value. In order to examine this, the fungible weights procedure was run on all 402 regressions with complete, positive definite, correlation matrices using an alternative model R^2 that was 99% the size of the OLS model R^2. This meant that the absolute loss in R^2 between the optimal and alternative weight models ranged from 0 to 0.009, so the models in these analyses had a smaller reduction than the models reduced by a constant of 0.01. To see the full distribution of the absolute loss in R^2 see Figure 20. Keeping the percent of the reduction in R^2 constant, made $cos\measuredangle \boldsymbol{k}_i O \boldsymbol{k}_j$ a constant value across all regressions, in this case, it was equal to 0.99.

With the 1% reduction, 55 (13.68%) regressions had all 5000 alternative weight vectors produce the same rank of the variables according to weight that was present in the OLS solution vector, 117 (29.10%) of the regressions had 1000 or less alternative weight vectors preserve the entire rank. A full distribution of the results across the 402 regressions of the number of vectors preserving this order (out of the 5000 alternative weight vectors produced for each regression) can be seen in Figure 21. When examining just the top ranked weight and whether or not that remained associated with the same variable across alternative weighting vectors, the results were more favorable. A total of 205 (51.00%) regressions had all 5000 alternative vectors assign the same variables the largest weight as in the OLS weight vector. None of the regressions had 1000 or less alternative weight vectors preserve the top ranked variable. A full distribution for the number of vectors (out of 5000) that preserved the top ranking can be seen in Figure 22.

As with the 0.01 reduction condition, the Kendall's τ between the rank order of the predictors according to the OLS weights and alternative weights was calculated for each alternative weight vector and averaged across the 5000 alternative vectors for each regression where the model R^2 was reduced by 1% . The distribution of these average correlations can be seen in Figure 23. The distribution has a mean of 0.90 and a standard deviation of 0.10. This distribution highlights the fact that while $cos\measuredangle \boldsymbol{k}_i O \boldsymbol{k}_j$ remains constant, the agreement between the rank order of the optimal and alternative weights still varies across regressions.

Given the past focus on the performance of unit weights in the literature some might wonder how the performance of unit weights may relate to the sensitivity of weights as examined through the fungible weights procedure. The R^2 produced by unit weights was compared to the R^2 produced by the OLS weights. Recall that weights of 1 were assigned to predictors where $r_{\boldsymbol{yx}_i}$ was greater than 0 and -1 where $r_{\boldsymbol{yx}_i}$ was less than 0. The R^2 for the unit weighted models were calculated according to the methods laid out in Dana and Dawes (2004). The distribution of the difference between these two R^2 can bee seen in Figure 24. When looking at the raw differences it might seem as if there is generally only a small reduction (depending on your particular field of study) in R^2 for models with unit weights compared to models with OLS weights (mean=0.11) , however this metric ignores the initial size of the OLS model R^2. To get an idea of the magnitude of the difference the percent reduction of the R^2 from the OLS weights model to the unit weight model was examined. The full distribution of this percent reduction can be seen in Figure 25. The percentage reductions are more normally distributed across regressions with an average reduction in R^2 of 34.95% when going from the OLS weights to the unit weights.

Some might theorize that models where unit weights perform comparatively well are likely to be more insensitive to shifts in weights- perhaps making the investigation of alternative weight vectors through fungible weights unnecessary. In order to investigate this, the relationship between the change in the model R^2 between models with OLS weights and unit weights and the results of the fungible weights analysis was examined. The correlation between the change in R^2 between OLS and unit weights and the average kendall's τ was 0.40. A scatterplot of this relationship is presented in Figure 26. It is notable that only a small subset of models (6.72%, to be precise) show a decrease in R^2 less than 0.01, which was the reduction in R^2 used in the fungible weights analysis that produced the kendall's τin the scatterplot. The correlation and the scatterplot show a small positive relationship between the reduction in R^2 between OLS weights and unit weights and a model's insensitivity to changes in weights. These results might feel counter intuitive. Because unit weights are a particular form of alternative weights, models that are more robust to one set of alternative weights might be expected to be more robust to other (and in this case a wider variety of) alternative weighting schemes. However, examination of the scatterplot shows that testing unit weights is not a replacement for examining fungible weights. Some models with a smaller difference in loss of model fit when comparing unit and optimal weights show a fairly small difference in ranking (a high average kendall's τ) when comparing OLS and alternative weights, indicating that weights need to stay relatively similar to preserve model fit indices despite the small change in R^2 when using unit weights. This also makes sense- unit weights are just one instance of possible alternative weighting schemes. Examining the change in model fit for a single alternative weight vector does not replace evaluating the set of alternative weight vectors produced by a pre-determined reduction in model fit.

4.4 Simulation Study

Individual regressions from 5 articles were chosen for a deeper look at weight sensitivity. The top 3 most highly cited articles that drew conclusions based on the size of the beta weights were chosen as well as the top 2 most highly cited articles that conducted a relative importance analysis. The sensitivity analysis showed the range of model sensitivity for the regressions examined in this study. However, the sensitivity analysis did not necessarily provide a sensible baselines for regression users looking to compare their model's sensitivity to the sensitivity of other, similar models.

In this simulation, similar models were defined as models that had the same values for $\boldsymbol{\beta}$ and R^2. In order to do this, for each regression examined 1000 predictor correlation matrices were produced using the FungibleR function (Waller, 2016). The values of $\boldsymbol{\beta}$ and R^2 were held constant, only the values in the various $\boldsymbol{R}^*_{\boldsymbol{X}}$ were allowed to differ, with the only further constraint on $\boldsymbol{R}^*_{\boldsymbol{X}}$ being that $\boldsymbol{R}^*_{\boldsymbol{X}}$ remain positive definite. At this point it is clear that $cos\measuredangle\boldsymbol{k}_i O\boldsymbol{k}_j$ will remain the same across these conditions, given that R^2 and the reduction in R^2 will be held constant. You can see the relationship between model R^2 and $cos\measuredangle\boldsymbol{k}_i O\boldsymbol{k}_j$ in Figure 27. Once a model approaches an R^2 of about 0.2, $cos\measuredangle\boldsymbol{k}_i O\boldsymbol{k}_j$ shoots up at a rapid rate.

Remember by examining the alternative vectors produced by the fungible weights analysis only a sample of alternative weight vectors from an infinite pool are being studied. Metrics based on this sample of alternative vectors can vary from sample to sample, even when all inputs remain constant. In order to be able to sensibly compare the results of running the fungible weights analysis using 1000 $\boldsymbol{R}^*_{\boldsymbol{X}}$, the fungible weights analysis was also run 1000 times using the original $\boldsymbol{R}_{\boldsymbol{X}}$.

The first regression examined came from Mumford et al. (2008), this regression was used to draw conclusions based on the size of the beta weights and was discussed above in regard to relative importance metrics. The regression with task role performance as the criterion was run through the simulation. When looking at the average τ distribution it is clear that the distribution produced by running the original regression through the fungible weights procedure 1000 times (let's call this the fungible weights distribution) is different than the distribution of the average τ produced by running 1000 $\boldsymbol{R}_{\boldsymbol{X}}^{*}$ (let's call this the fungible R distribution) through the fungible weights procedure. The fungible weights distribution of the average τ can be seen in Figure 28. A vertical line is present at the median point for the fungible R distribution. The fungible R distribution of the average τ with a vertical line at the median for the fungible weights distribution can be seen in Figure 29. None of the average τ's in the fungible weights distribution fall below the median for the fungible R distribution. Conversely, 84.17% of the average τ's in the fungible R distribution fall below the median value of the average τ for the fungible weights distribution. These results indicate that among models with the same values of $\boldsymbol{\beta}$ and $\boldsymbol{R}^2$, this regression from Mumford et al. (2008) is doing pretty well in regards to having alternative vectors that maintain the same ranking of the beta coefficients.

The next regression examined was from Dabos and Rousseau (2004) this regression was used to draw conclusions based on the size of the beta weights and was discussed above in regard to relative importance metrics. The fungible weights distribution of the average τ with a vertical line at the median point for the fungible R distribution can be seen in Figure 30. The fungible R distribution of the average τ with a vertical line at the median for the fungible weights distribution can be seen in Figure 31. These distributions are similarly shaped to those seen in Mumford et al. (2008), however the comparison is quite different. It is still true that none of the average τ's in the fungible weights distribution fall below the median for the fungible R distribution. However, 64.50% of the average τ's in the fungible R distribution fall below the median value for the fungible weights distribution. In this case it looks like the regression from Dabos (2004) is not doing nearly as well as the one examined above from Mumford et al. (2008) in regards to rank order shifts among alternative weight vectors when compared to similar regressions.

Next a regression from Klehe and Anderson (2007) was examined, this regression was used to draw conclusions based on the size of the beta weights and was discussed above in regard to relative importance metrics. The fungible weights distribution of the average τ with a vertical line at the median point for the fungible R distribution can be seen in Figure 32. The fungible R distribution of the average τ with a vertical line at the median for the fungible weights distribution can be seen in Figure 33. It is still true that none of the average τ's in the fungible weights distribution fall below the median for the fungible r distribution. In this case, 88.29% of the average τ's in the fungible R distribution fall below the median value for the fungible weights distribution. The regression examined here from Klehe and Anderson (2007) is doing better than the other regressions examined thus far in regards to rank order shifts among alternative weight vectors when compared to similar regressions.

The next regression came from Jiang, Lepak, Hu, and Baer (2012), a meta analysis that investigated the relationship between various dimensions of HR systems and organizational outcomes. The selected regression regressed human capital onto skill-enhancing HR practices, motivation-enhancing HR practices, and opportunity-enhancing HR practices. The authors also used relative weights to determine what percent of variance explained was associated with each predictor. They concluded "the analyses of relative weights indicate that skill-enhancing HR practices explained the largest percentage of variance in human capital (48%), followed by motivation-enhancing HR practices (36%) and opportunity-enhancing HR practices (16%)" (p.1272). The article had been cited 514 times as of February 24, 2017. The fungible weights distribution of the average τ with a vertical line at the median point for the fungible R distribution can be seen in Figure 34. The fungible R distribution of the average τ with a vertical line at the median for the fungible weights distribution can be seen in Figure 35. It is still true that none of the average τ's in the fungible weights distribution fall below the median for the fungible R distribution. In this case, 80.60% of the average τ's in the fungible R distribution fall below the median value for the fungible weights distribution. The regression examined here from Jiang et al. (2012) is doing worse than those examined from Mumford et al. (2008) and Klehe and Anderson (2007) in regards to rank order shifts among alternative weight vectors when compared to similar regressions.

The last regression came from Richards and Schat (2011). The regression examined was the final step of a hierarchical regression that regressed emotional support seeking onto age, gender, positive affectivity, negative affectivity, extraversion, agreeableness, conscientiousness, emotional stability, openness, organizational commitment, attachment anxiety, and attachment avoidance. The authors conducted a relative weights analysis to determine what percent of variance explained was associated with each predictor. The authors found that "Attachment anxiety uniquely predicted ... and emotional support seeking (β=.39, R2 .08), F(1, 134) =24.51, p $<$ .001, beyond the control variables" (p.176) and that "Attachment avoidance also uniquely predicted emotional support seeking (β=-.38, ΔR^2 = .09), F(1, 134) = 28.21, p .001, with relative weights analysis showing that it was the strongest predictor, accounting for 23.1% of the total variance explained (R^2 = .13)" (p.176). The article has been cited 128 times as of February 24, 2017. The fungible weights distribution of the average τ with a vertical line at the median point for the fungible R distribution can be seen in Figure 36. The fungible R distribution of the average τ with a vertical line at the median for the fungible weights distribution can be seen in Figure 37. It is still true that none of the average τ's in the fungible weights distribution fall below the median for the fungible R distribution. In this case, 90.70% of the average τ's in the fungible R distribution fall below the median value for the fungible weights distribution. The regression examined here from Richards and Schat (2011) is doing better than the other regressions examined in this simulation in regards to rank order shifts among alternative weight vectors when compared to similar regressions.

These simulations provide one option for how you can compare the sensitivity of one regression model to other, similar models. The simulations also demonstrate that even when R^2 and $\boldsymbol{\beta}$ are kept constant models can have different levels of sensitivity to changes in weights. Summary metrics from all of the above simulations can be found in Table 13.

5 Discussion

5.1 Summary of Results

In this study we have seen a sample of how regression is used in the I/O and general psychology literature, investigated the agreement of various relative importance metrics, looked into how to examine model sensitivity, and demonstrated that examining model sensitivity can can call into question conclusions drawn in the published literature. Regression has been and continues to be used across a wide variety of subject areas within psychology. The articles that use regression have been cited many times, indicating the influence of this literature on other published findings. Conclusions drawn from regressions often focus on the significance and sign of the coefficients as well as the model R^2. Conclusions based on the size of the coefficients are comparatively less common but still occur. The use of relative importance metrics is fairly rare with less than 5% of the articles examined using some kind of relative importance analyses. Only dominance analysis and relative weights were seen in this literature review. Surprisingly, and worthy of concern was the finding that many articles that published regression models did not include full correlation matrices for the predictor and criterion variables, making it difficult for readers to critically examine the regression model with the added information provided by bivariate correlations.

Using published literature to examine the agreement between various relative importance metrics revealed that these metrics, while all positively correlated, can and do lead to different conclusions. The agreement between the full rank order of the predictors varied depending on the pair of metrics examined, but all pairs showed at least some disagreement on rank. When examining the more narrow question of whether or not these metrics agree on the most important predictor in a model it was discovered that in the regressions studied more than half of the time they do not. While all metrics reviewed in this paper ostensibly aim to answer the question "What is the most important predictor in a model?" it was clear at the outset of the study that each measure was operating with a unique definition of importance. The findings here emphasize that these differences in definitions and approaches to measuring relative importance are not trivial and do provide different conclusions. It is important that choice of relative importance metric ensures that the definition of importance is aligned with the research question.

In the sensitivity analysis it became clear that the models reviewed varied in their insensitivity to rank shifts in their weights. Models that were insensitive to rank shifts had large variations in predictor rankings according alternative weight vectors despite having similar model fit indices to the original OLS model. It was also shown that relative importance analyses are not a replacement for examining model sensitivity. In some cases, even when all relative importance analyses examined agreed on the most "important" predictor, alternative weight vectors disagreed with the OLS weight vector regarding which variable was associated with the largest coefficient.

Two approaches were taken to model fit reduction. In the first approach alternative models explained 1% less of the variance in the dependent variable, in other words the model R^2 was reduced by a constant value of 0.01. Considering that some model R^2 were quite low, to the point that a 0.01 reduction might be considered a large portion of variance explained, all models were also put through fungible weights analyses where the model R^2 was reduced by 1%. In this condition the alternative model R^2 was 99% the size of the optimal model R^2. Less variation in the rank ordering of weights was observed when the model R^2 was reduced by 1% as opposed to a constant of 0.01. This was expected since the reduction of 1% in the R^2 resulted in a smaller absolute reduction in model fit than when all model R^2 were reduced by 0.01. Under both conditions there was still variance across models in terms of sensitivity to shifting rank order.

When examining the questions of whether or not alternative vectors agreed with the OLS vector on the top ranked predictor is was found that only 23.51% of regression models in the 0.01 reduction condition had all 5000 alternative vectors agree on the largest predictor, this went up to 51.00% for the 1% reduction condition. The numbers plummet to 3.87% (0.01 reduction) and 13.68% (1% reduction) when looking at how many models had the entire rank order of predictors preserved across all alternative models. These findings emphasize the difficulty of drawing meaningful conclusions based on the relative size of regression coefficients given that the rankings of the predictors can shift drastically in the face of only small model fit reductions. Given that it is common for models to be associated with alternative weight vectors that do not even agree with the OLS model on which predictor is associated with the largest coefficient conclusions based on coefficient size should be questioned. It is worth noting how other metrics that use regression coefficients to draw conclusions (e.g. the pratt measure) will experience similar difficulties.

The simulation study provided one possible example of how to evaluate the level of a model's sensitivity to rank shifts in the weights. The simulation compared a model's variance in predictor rank to similar model's variance in predictor rank, where model R^2 and the β_i were kept constant. Along with providing one method of comparing the results of the fungible weights analysis for a given model to similar models as defined by variance explained and optimal weights, the simulation also demonstrated how varying the correlation matrix of the variables in the regression impacts the results of fungible weights analyses.

5.2 Limitations and Areas for Future Research

The results presented in this paper are not without limitations. The sample of regressions come from a particular subset of the literature, it was designed to be a systematic review of an influential sample of recent I/O, Human Resources, and general psychology related studies. While the inclusion criteria were thoughtfully designed, this review is a sample and not meant to be an exhaustive description of the population of all studies in I/O, human resources, or general psychology. The paper aimed to provide a demonstration on a meaningful sample rather than a complete statement on the state of OLS in regression in psychology. This study focuses on a narrow slice of regression, with fairly stringent inclusion criteria. The inclusion criteria were designed to both sample from a meaningful slice of the literature while also maximizing the chance that articles included in the database of past literature could be included in further quantitative analysis. The inclusion criteria for this study means that this paper did not tackle non-OLS regression or regressions that included interaction and exponential terms. It is easy to see how the findings presented in this paper could be applied beyond the scope of the inclusion criteria. Indeed, fungible weights has already been extended to apply to logistic regression (Jones, 2013), latent curve models (McCallum, Lee, & Brown, 2012), and structural equation models (Lee & MacCallum, 2015; MacCallum, Browne, & Lee, 2009; Pek, 2012) as well as studied with regards to implications for mediation analysis (Agler, 2015). If the correlations between interaction or exponential terms and the other variables in the model are known the procedures used in this paper can be directly applied. Future research could focus on the applying sensitivity analyses to more complex models and dissecting the conclusions from those models.

The study did not focus on issues related to cross-validation, in fact that analyses in this study were independent of sample size and therefore did not touch on issues related to sampling variability. While the purpose of this study was to emphasize that there are issues with interpreting regression independent of sampling choices there are avenues for future research concerning how relative importance metrics behave across samples and working to determine what factors are related to a predictor's importance remaining constant across samples.

The analyses were based on published findings which in and of themselves can be flawed due to typos and rounding error. Not to mention that published studies may not be representative of the larger set of research being done due to publication bias. The data for this study was entered by hand and although data entry was done carefully and data was checked multiple times there is always a chance, especially when it comes to entering as many individual numbers as in the present study, that data entry errors may have occurred and impacted the results.

A subset of relative importance metrics were chosen to study, but more exist in the literature, and I strongly suspect more will continue to be proposed. Rather than presenting a single best indicator of importance this study was meant to be a review and observation of these metrics in practice. Those wishing for one definitive answer regarding what predictor is most important in their regression mode will find this study wanting.

The sensitivity analysis chose to only examine 2 possible values for each regression for the reduction in model fit. Subjective decisions were made regarding what can be considered a trivial reduction in model R^2. While I believe these reductions were small and chose to examine two types of reductions to ensure this, some may argue that the reductions in this study represent large losses in explanatory power of the model and therefore the findings regarding sensitivity do not apply. Future studies could look at increasing the variation in reduction of model fit.

The simulation relating to model sensitivity run in this study provided a very specific comparison, restricting the model fit and original model weights. In terms of model inputs, this only allowed for variation in the correlation matrix. Some might be more interested in how a specific model compares to all other models with the same number of predictors, or all models with the same model fit. Varying different aspects of the model will provide different result distributions and the performance articles examined will depend on the specific comparison group. Future research could compare results across a number of different situations with a variety of combinations of parameters that are held constant and allowed to vary.

5.3 Practical Implications

This paper makes it clear that I/O psychology has a large problem with presenting the findings of OLS regression. This study emphasizes the need for careful consideration and definition of the goals of a study before undertaking analyses. This paper has presented a set of tools to use, and explained their variations and nuances, in what is hoped to be an easily consumable manner. Regression is a tool that solves a very specific problem, it provides a linear model using the given predictors and criterion that is optimized with respect to minimizing the squared errors in the prediction of the criterion value. It has been made clear in past literature that in many instance OLS regression weights are not the best weights for providing accurate prediction in a future sample. This is not surprising given that the goal of OLS regression is not to optimize performance in a cross validation framework. The current study demonstrated that when different definitions of importance are used to create relative importance metrics, those metrics will often disagree on what predictor is determined to be most important. Examining the sensitivity of the regression models to changes in predictor weights indicated that the regression models included in this study were generally insensitive to weight shifts and were able to maintain similar model fit indices even when predictor weights were varied. In some instances unit weights showed a relatively low reduction in model R^2.

Given what is known about regression and the findings from the current study, when considering using regression it makes sense to stop and ask a few questions:

1. Have I designed my study well?

   Methods of analysis are not a fix for flaws in methodology. It is much easier to control for alternative explanations through study design rather than working to partial out effects post-hoc.

2. What question am I trying to answer with my study?

   Be specific. General questions like "I want to investigate the relationship of the variables" can lead to confusion later on. What can you see by looking at the correlation matrices, and what is it that you are trying to find beyond a bivariate correlation?

3. Do I want a model that is going to do well in my current sample or one that I can successfully apply to new samples?

   If the goal is prediction in new samples, OLS regression is not your best choice. Look at analyses that are designed to optimize prediction in new samples, rather than optimized for describing the current sample.

4. Am I going to try make a statement regarding what is important in my model? If so, what do I mean by importance?

Do you define a variable's importance in relationship to the other variables included in the model or do you want a measure of importance based simply on the relationship between a given predictor and the criterion. Is it important for a predictor's importance to be based on all possible models that can be built with the given predictors or just the model with all predictors included? If all possible models are important, are you interested in directly comparing each variable to every other variable, such as is possible with dominance analysis?

5. Is my model sensitive to changes in weights?

   There are no precise guidelines here. But if you are planning to make a conclusion about the size, or even the sign of your weights, it makes sense to examine weight vectors that will produce a similar model fit and think about if the conclusions drawn from original model would hold given the characteristics of these alternative vectors. If a given predictor has a positive weight in the OLS model but a negative weight in a subset of alternative weight vectors that only reduce the model fit by a small amount, how strong are conclusions based on the sign of the coefficient? Similarly, if conclusions are drawn based on how large a specific β_i is in isolation or in comparison to other predictors, if the alternative weight vectors result in largely different values and ranks for the predictor it is difficult to be confident about a conclusion drawn based on the initial value of β_i. This study has shown that alternative models in I/O, HR, and psychology can be quite different from optimal ones, it is important to leverage knowledge about a model's sensitivity when interpreting findings.

Based on the literature reviewed in this study the following 2 recommendations would help to improve published studies that use regression analyses:

1. Do not draw conclusions based solely on the size of the β_i's.

   β_i are the coefficients that minimize SSE for a specific model in a specific sample. Unless the research question is very specific to this use case, do not use the size of the β_i's to draw conclusions. The studies examined in the current paper that drew conclusions based on the size of the β_i were not seeking to answer questions that aligned with the specific meaning of OLS weights. Instead they used β_i as a proxy to indicate a more general construct of importance. It is clear from past research and the current study that the size of the β_i's can vary based on sample characteristics, and can change if you slightly loosen the requirement to minimize SSE. SIOP (2003) has previously highlighted the dangers of optimal weights in regards to sampling variability but has not yet emphasized the difficulties that arise when you consider model sensitivity. The literature and the field will benefit from emphasizing the drawbacks associated with β_i's. Instead of focusing on the raw value, sign, or even significance of β_i's consider discussing what approaches would result in different conclusions and the sensitivity of a given model to changes in weights.

2. Always provide full correlation or covariance matrices for all variables used in a regression model.

   Correlation matrices are important, and savvy readers will often examine the correlation matrices before moving on to more complex models. Correlations allow readers to draw their own conclusions based on the data and conduct follow up analyses if desired. Publishing correlation matrices also allow for easy data collection for future meta-analyses.

By consistently considering the above questions and following the stated recommendation I/O psychologists will vastly improve the way OLS regression is handled in the published literature. There is reason to believe this will have positive effects in the applid world and the training of new I/O psychologists in the future.

5.4 Concluding Remarks

OLS regression has been and continues to be a popular tool in applied and academic realms of I/O psychology (e.g. Stone-Romero et al. 1995, O'Neill et al., 2013). OLS regression has often been the subject of criticism regarding its ability to produce similar results across samples, the complicated or at least misunderstood meaning behind the predictor weights, and the question of its value-add when compared to other metrics. A variety of metrics have been proposed as methods of determining what predictor is the most "important" variable in a given regression model. Each of these relative importance metrics has garnered praise and criticism from different camps. I would argue that the issue does not lie with the tools themselves, as it may seem based on some of the criticisms. Each method is designed with specific goals and each method does produce a result that answers a question (although the question answered may not be the one initially intended). The issues lie instead, with the applications of these tools. It seems that consumers of these tools have often conducted analyses without carefully considering what insights they hope to gain. This is understandable given that thinking about what question is driving research, and what is actually considered valuable can be deceptively complicated. It is also reasonable to see how the meaning of predictor importance would be considered an intimidating pursuit since past definitions and approaches to quantifying importance have been subjected to harsh scrutiny.

When thinking about variable importance it is much easier to make the statement "I need to know the most important variable in this model" rather than to consider the nomological net of what constitutes variable importance and the metrics associated with the different facets of this construct. For example Duckworth and Seligman (2005) state that "the standardized regression coefficient of self-discipline was more than twice that of IQ in a simultaneous multiple regression predicting final GPA. These results suggest that, indeed, self-discipline has a bigger effect on academic performance than does intellectual talent" (p. 942-943). In this instance, as in others, effect has been defined by the size of β_i. Defining effect or importance by the size of β_i is akin to defining depression as the score on a depression inventory without first going into extensive details about how the scale was constructed and what definition of depression the scale was set out to measure. Statements about the results of a regression equation are often presented without much comment on how the specific results should be interpreted. This seems to suggest that there is an assumption of a universally agreed upon meaning for regression results, however that is clearly not the case. Past literature has demonstrated the danger of interpreting the size of regression weights, but as was demonstrated in this study, the size of regression weights are still being used to formulate conclusions. While the majority of articles reviewed did not make statements regarding the size of the regression weights, those that did were cited, on average, 518 times (as of February 24, 2017). This indicates that even if interpreting the size of regression weights in published literature is rare, the influence of findings based on these interpretations is large. Many authors, and likely many readers, have been influenced by articles that use the values of β_i to draw conclusions. Given that these articles were published in highly regarded journals, consumers of these articles may be under the impression that drawing conclusions based on the values of β_i is acceptable and perhaps even encouraged. Given that influential articles draw conclusions based on the size of the β_i, simply publishing β_i without a clear discussion of the purpose of the weights, could lead to readers misinterpreting results.

The current study focused on published literature but it is important to emphasize that regression is a frequently used tool in applied I/O as well. It is difficult, if not impossible, to quantify the effect of regression in the applied domain but it is possible to consider a specific example. Thinking back to the introduction of this paper, a common question for an applied I/O psychologist is "What is most important in driving employee engagement?". Many practitioners may begin by creating a regression model that has employee engagement scores as the dependent variable and all possible predictors of engagement in their database as predictors. It is possible that the next step would be to look at the model R^2 in order to get an idea about how much variance in employee engagement is able to be explained by the included predictors. This R^2 is likely inflated in comparison to the relationship you would expect to see in the population since it is capitalizing on sample characteristics. The R^2 can be adjusted based on sample size and number of predictors with the assumption being that this new adjusted R^2 (if using the correction proposed by Wherry (1931)) would be reflective of the R^2 that would be observed if this model was applied to the whole population.

The practitioner might briefly examine the R^2 to ensure that the included variables were accounting for enough variance in engagement in order for the analysis to move froward. However, the R^2 will only demonstrate if that combination variables is related to engagement, not what is the most important driver. Next the practitioner might examine the values in $\boldsymbol{\beta}$. The practitioner may remember reading some articles, in highly regarded journals, where the authors indicated that larger values of β_i meant that the associated predictor was more important. Perhaps the practitioner also recalls taking a statistics course where the instructor discussed how β_i is the expected change in the dependent variable given a one unit change in the predictor, holding all other predictors constant, and with all variables in the model transformed into z scores. Perhaps the practitioner stops here and and tells his or her clients that the variable most important for driving engagement is the one associated with the largest β_i.

Maybe the practitioner keeps going, he or she has gone to a few conferences and knows that there are newer methods associated with determining relative importance. In fact the practitioner remembers that dominance analysis takes into consideration all possible subsets. All possible subsets may seem appealing given that the model might have been built without much thought being put into what variables were included in the model. So the practitioner runs a dominance analysis. If there are a lot of variables in the model and limited computing resources the dominance analysis may not run, in which case the practitioner might run a relative weights analysis. Since relative weights is meant to be a more computationally efficient form of dominance analysis, this seems like the right choice. The practitioner might be feeling good at this point. First order correlations seem basic, $\boldsymbol{\beta_i}$ have a large literature associated with their flaws, and these new analyses appear to be cutting edge. The practitioner presents the findings of the relative weights analysis to his or her stakeholders. The practitioner is able to decide which variable is most important by making a statement about what percent of the explained variance is able to be attributed to each predictor. The results of these analyses gives a nice balance of information that appears to be easy to understand while still implying technical expertise.

No matter choice the practitioner makes in terms of how to determine what variable is most important, a critical step has been missed in this thought experiment. There has not been a discussion of how the findings of these analyses will be used. In the applied world analyses are generally not done due to academic curiosity, analyses are used to make decisions regarding action planning. Stakeholders often want to know what drives employee engagement so that plans can be made to increase engagement through leveraging these drivers. The way in which these action plans are going to be formulated, however, can be an important piece of information. If the stakeholders want to focus on changing a single factor related to employee engagement it might make sense to choose the predictor with the largest bivariate correlation with engagement. If the stakeholders want to focus on 2 or 3 things, it may make sense to look into model selection and find the set of 2 or 3 predictors that account for the largest variance in engagement. Brainstorming how the findings of a study could be used, before beginning the study, is an important step in ensuring the right choice in analytic techniques.

Regression models have played a large role in establishing the field of I/O psychology. It is imperative that users and consumers of regression continue to scrutinize the findings from these models. Models that are able to withstand large shifts in weights with small changes in fit indices call into question the meaning of the coefficients in these models. The sensitivity of a model to shifts in weights is a product of the mathematical basis of the model itself and cannot be remedied by approaches recommended to mitigate sampling variability such as increasing sample size. By carefully examining our analyses, using the steps laid out in this paper, we will gain a better understanding of how to interpret and present our results. Acknowledging and examining the strengths and weaknesses in our analyses will enable us to make stronger conclusions and progress as a field.

References

Abadir, K.M., & Magnus, J.R. (2002). Notation in econometrics: A proposal for a standard. *Econometrics Journal, 5,* 76–90.

Agler, R. A. (2015). *Topics in Testing Mediation Models: Power, Confounding, and Bias* (Doctoral dissertation, The Ohio State University).

Amado, A. J. (1999). *Partitioning predicted variance into constituent parts: A primer on regression commonality analysis.* Paper presented at the annual meeting of the Southwest Educational Research Association, San Antonio, TX

Azen, R., & Budescu, D. V. (2003). The dominance analysis approach for comparing predictors in multiple regression. *Psychological Methods, 8*(2), 129-148.

Bass, B. M. (1990). Bass and Stogdill's Handbook of Leadership. New York: Free Press.

Bobko, P. (Ed.). (2001). *Correlation and regression: Applications for Industrial Organizational Psychology and Management.* Sage.

Bobko, P., Roth, P. L., & Buster, M. A. (2007). The usefulness of unit weights in creating composite scores a literature review, application to content validity, and meta-analysis. *Organizational Research Methods, 10*(4), 689-709.

Budescu, D. V. (1993). Dominance analysis: A new approach to the problem of relative importance of predictors in multiple regression. *Psychological Bulletin, 114*(3), 542-551.

Cascio, W.F., & Aguinis, H. (2008). Research in industrial and organizational psychology from 1963 to 2007: Changes, choices, and trends. *Journal of Applied Psychology, 93*(5), 1062-1081.

Cicchetti, D. V. (1994). Guidelines, criteria, and rules of thumb for evaluating normed and standardized assessment instruments in psychology. *Psychological Assessment, 6*(4), 284-290.

Cohen, J., 1994. The earth is round ($p < .05$). *American Psychologist, 49*(12), 997-1003.

Cohen, J., Cohen, P., West, S. G., & Aiken, L. S. (2003). *Applied multiple regression/ correlation analysis for the behavioral sciences* (3rd ed.). Mahwah, NJ: Lawrence Erlbaum Associates, Inc.

Cortina, J.M., & Landis, R.S., 2011. The earth is not round ($p = .00$). *Organizational Research Methods, 14*(2), 332-349.

Courville, T., & Thompson, B. (2001). Use of structure coefficients in published multiple regression articles: β is not enough. *Educational and Psychological Measurement, 61*(2), 229-248.

Dana, J., & Dawes, R. M. (2004). The superiority of simple alternatives to regression for social science predictions. *Journal of Educational and Behavioral Statistics, 29*(3), 317-331.

Darlington, R. B. (1968). Multiple regression in psychological research and practice. *Psychological Bulletin, 69*(3), 161-182.

Davis-Stober, C. P. (2011). A geometric analysis of when fixed weighting schemes will outperform ordinary least squares. *Psychometrika, 76*(4), 650-669.

Dawes, R. M. (1979). The robust beauty of improper linear models in decision making. *American Psychologist, 34*(7), 571-582.

Green, B.F., 1977. Parameter sensitivity in multivariate methods. *Multivariate Behavioral Research, 12,* 263-287.

Harris, R. J. (2001). *A primer on multivariate statistics* (3rd ed.). Mahwah, NJ: Erlbaum.

Hoyt, W. T., Leierer, S., & Millington, M. J. (2006). Analysis and interpretation of findings using multiple regression techniques. *Rehabilitation Counseling Bulletin, 49*(4), 223-233.

Johnson, J. W. (2000). A heuristic method for estimating the relative weight of predictor variables in multiple regression. *Multivariate Behavioral Research, 35*(1), 1-19.

Johnson, J.W., & Lebreton, J.M. (2004). History and use of relative importance indices in organizational research. *Organizational Research Methods, 7*, 238-257.

Jones, J. A. (2009). GenCorr: An R Routine to Generate Correlation Matrices From a User-Defined Eigenvalue Structure. *Applied Psychological Measurement*, *34*(1), 68-69.

Jones, J. A. (2013). *Fungible weights in logistic regression* (Doctoral Dissertation, University of Minnesota).

Jones, J. A., & Waller, N. G. (2013). Computing confidence intervals for standardized regression coefficients. *Psychological Methods, 18*(4), 435-453.

Judge, T. A., Bono, J. E., Ilies, R., & Gerhardt, M. W. (2002). Personality and leadership: a qualitative and quantitative review. *Journal of Applied Psychology, 87*(4), 765.

Judge, T. A., Higgins, C. A., Thoresen, C. J., & Barrick, M. R. (1999). The big five personality traits, general mental ability, and career success across the life span. *Personnel Psychology, 52*(3), 621-652.

Koopman, R.F., 1988. On the sensitivity of a composite to its weights. *Psychometrika, 53*(4), 547-552.

Kuncel, N. R., Hezlett, S. A., & Ones, D. S. (2004). Academic performance, career potential, creativity, and job performance: can one construct predict them all?. *Journal of Personality and Social Psychology, 86*(1), 148.

LeBreton, J. M., Ployhart, R. E., & Ladd, R. T. (2004). A Monte Carlo comparison of relative importance methodologies. *Organizational Research Methods, 7*(3), 258-282.

Lee, T., & MacCallum, R. C. (2015). Parameter influence in structural equation modeling. *Structural Equation Modeling: A Multidisciplinary Journal, 22*, 102–114.

Lievens, F., Ones, D. S., & Dilchert, S. (2009). Personality scale validities increase throughout medical school. *Journal of Applied Psychology, 94*(6), 1514.

MacCallum R. C., Browne, M. W., & Lee, T. (2009). *Fungible parameter estimates in structural equation modeling.* Paper presented at the Annual Meeting of the Psychometric Society. Salishan Resort, Oregon.

MacCallum, R. C., Lee, T., & Browne, M. W. (2012). Fungible parameter estimates in latent curve models. In M. C. Edwards, & R. C. MacCallum (Eds.), *Current issues in the theory and application of latent variable models* (pp. 183–197). Routledge Academic.

Nathans, L. L., Oswald, F. L., & Nimon, K. (2012). Interpreting multiple linear regression: A guidebook of variable importance. *Practical Assessment, Research & Evaluation, 17*(9), 2.

Nimon, K. (2011). Improving the quality of quantitative research reports: A call for action. *Human Resource Development Quarterly, 22*(4), 387-394.

Nimon, K. F., & Oswald, F. L. (2013). Understanding the Results of Multiple Linear Regression: Beyond Standardized Regression Coefficients. *Organizational Research Methods, 16*(4), 650-674.

Nimon, K., & Roberts, J.Ra. (2012). yhat: Interpreting regression effects (R package version 1.0-5) [Computer software]. Retrieved from http://CRAN.R-project.org/package1/4yhat

O'Neill, T. A., McLarnon, M. J., Schneider, T. J., & Gardner, R. C. (2013). Current misuses of multiple regression for investigating bivariate hypotheses: an example from the organizational domain. *Behavior Research Methods*, 1-10.

Pek, J (2012). *Fungible parameter contours and confidence regions in structural equation models.* (Unpublished doctoral dissertation). University of North Carolina at Chapel Hill.

Pratt, J. W. (1987, June). Dividing the indivisible: Using simple symmetry to partition variance explained. In Proceedings of the second international conference in statistics (pp. 245-260). Tampere, Finland: University of Tampere.

Raju, N. S., Bilgic, R., Edwards, J. E., & Fleer, P. F. (1997). Methodology review: Estimation of population validity and cross-validity, and the use of equal weights in prediction. *Applied Psychological Measurement, 21*(4), 291-305.

Raju, N. S., Bilgic, R., Edwards, J. E., & Fleer, P. F. (1999). Accuracy of population validity and cross-validity estimation: An empirical comparison of formula-based, traditional empirical, and equal weights procedures. *Applied Psychological Measurement, 23*(2), 99-115.

Ree, M. J., Earles, J. A., & Teachout, M. S. (1994). Predicting job performance: Not much more than g. *Journal of Applied Psychology, 79*(4), 518.

Ree, M.J., Carretta, T.R., & Earles, J.A. (1998). In top-down decisions, weighting variables does not matter: A consequence of Wilks' theorem. *Organizational Research Methods, 1*(4), 407-420.

Schmidt, F. L., & Hunter, J. (2004). General mental ability in the world of work: occupational attainment and job performance. *Journal of Personality and Social Psychology, 86*(1), 162.

Schmidt, F. L., & Hunter, J. E. (1998). The validity and utility of selection methods in personnel psychology: Practical and theoretical implications of 85 years of research findings. *Psychological Bulletin, 124*(2), 262.

Schmidt, F., 2010. Detecting and correcting the lies that data tell. Perspectives on Psychological science, 5(3), 233-242. Schmidt, F.L., 1971. The relative efficiency of regression and simple unit predictor weights in applied differential psychology. *Educational and Psychological Measurement, 31*(3), 699-714.

Sobel, M. E. (1990). Effect analysis and causation in linear structural equation models. *Psychometrika, 55*(3), 495-515.

Society for Industrial and Organizational Psychology. (2003). *Principles for the Validation and Use of Personnel Selection Procedures* (4th ed.).

Stone-Romero, E. F., Weaver, A. E., & Glenar, J. L. (1995). Trends in research design and data analytic strategies in organizational research. *Journal of Management, 21*(1), 141-157.

Thomas, D. R., Hughes, E., & Zumbo, B. D. (1998). On variable importance in linear regression. *Social Indicators Research, 45*(1-3), 253-275.

Thomas, D. R., Zumbo, B. D., Kwan, E., & Schweitzer, L. (2014). On Johnson's (2000) relative weights method for assessing variable importance: A reanalysis. *Multivariate Behavioral Research, 49*(4), 329-338.

Thompson, B., & Borrello, G. M. (1985). The importance of structure coefficients in regression research. *Educational and Psychological Measurement, 45*(2), 203-209.

Tonidandel, S., & LeBreton, J. M. (2010). Determining the relative importance of predictors in logistic regression: An extension of relative weight analysis. *Organizational Research Methods, 13*(4), 767-781.

Tonidandel, S., LeBreton, J. M., & Johnson, J. W. (2009). Determining the statistical significance of relative weights. *Psychological Methods, 14*(4), 387.

Wainer, H. (1976). Estimating coefficients in linear models: It don't make no nevermind. *Psychological Bulletin, 83*(2), 213-217.

Wainer, H. (1978). On the sensitivity of regression and regressors. *Psychological Bulletin, 85*, 267–273.

Waller, N.G. (2008). Fungible weights in multiple regression. *Psychometrika, 73*(4), 691-703.

Waller, N. G. (2016). Fungible correlation matrices: A method for generating nonsingular, singular, and improper correlation matrices for Monte Carlo research. *Multivariate Behavioral Research, 51*(4), 554-568.

Waller, N.G., & Jones, J.A. (2009). Locating the extrema of fungible regression weights. *Psychometrika,* 74(4), 589-602.

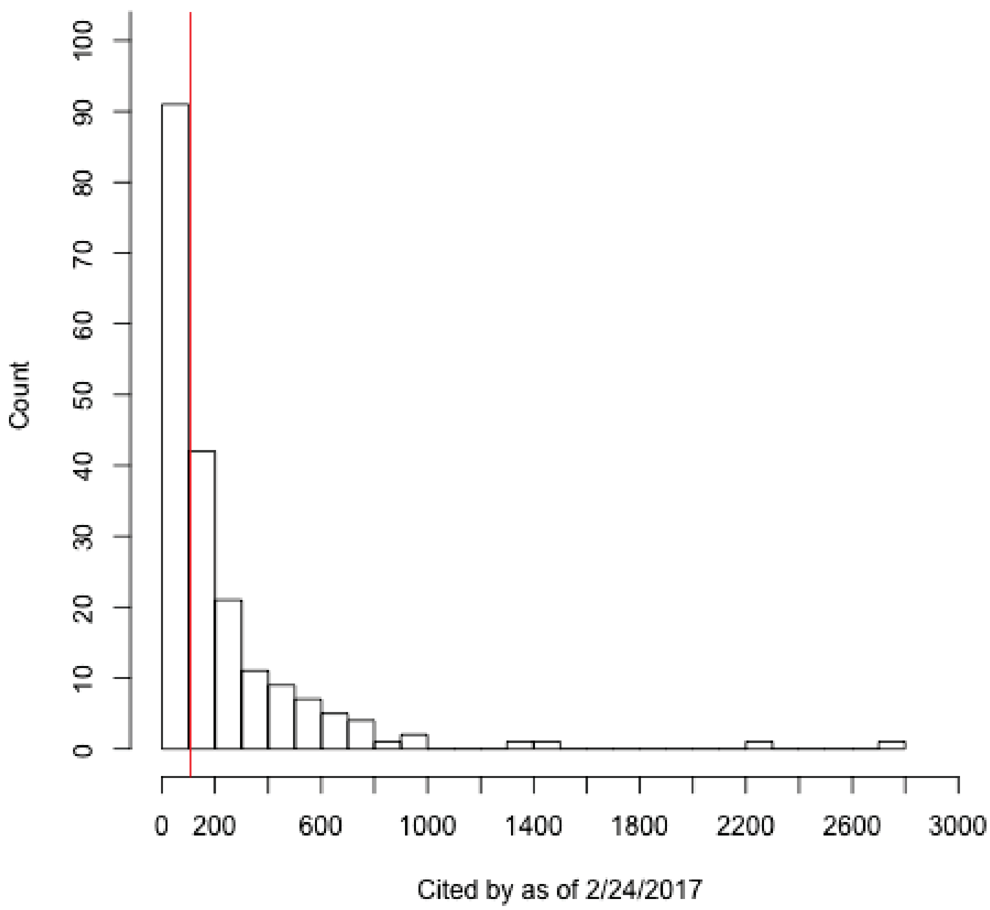
Wherry, R. (1931). A new formula for predicting the shrinkage of the coefficient of multiple correlation. *The Annals of Mathematical Statistics, 2*(4), 440-457.

Wilks, S.S. (1938). Weighting schemes for linear functions of correlated variables when there is no dependent variable. *Psychometrika, 3*, 23-40.

Zientek, L. R., & Thompson, B. (2006). Commonality analysis: Partitioning variance to facilitate better understanding of data. *Journal of Early Intervention, 28*(4), 299-307.

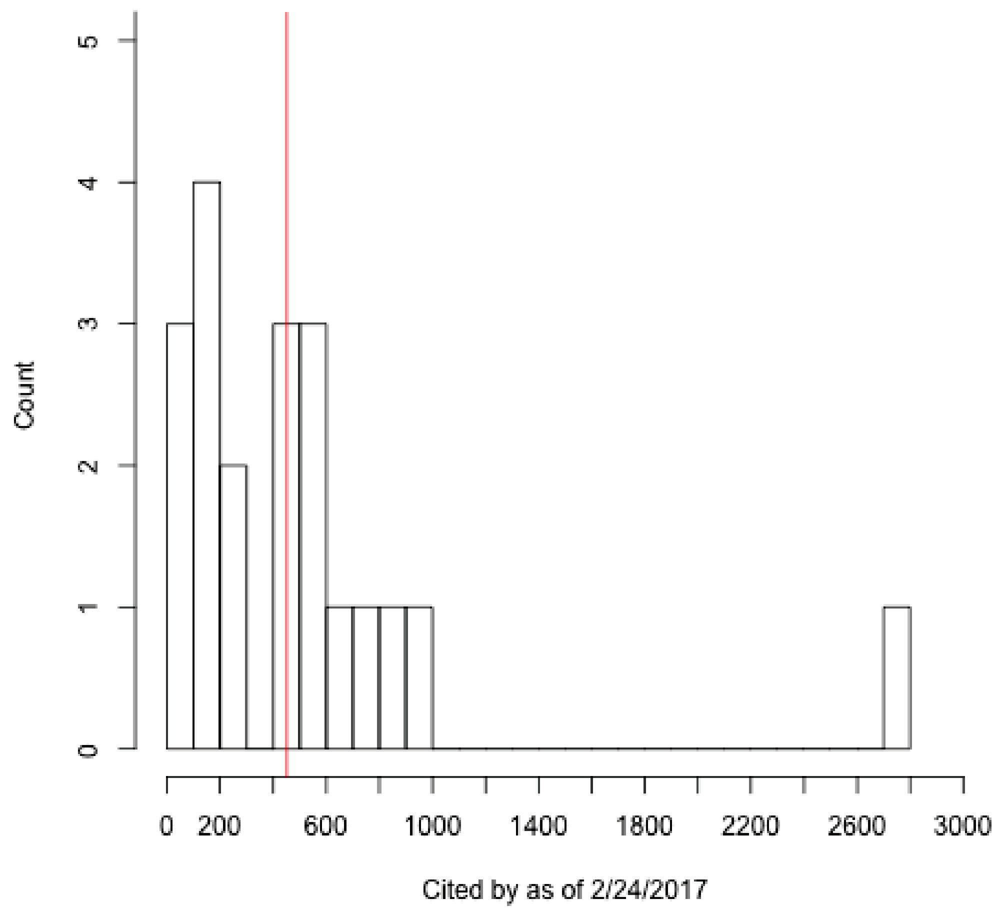
Zientek, L. R., Capraro, M.SM., & Capraro, R. M. (2008). Reporting practices in quantitative teacher education research: One look at the evidence cited in the AERA panel report. *Educational Researcher, 37*(4), 208-216.

Figure 1: Distribution of Number of Times Each Article Was Cited as of February 24, 2017



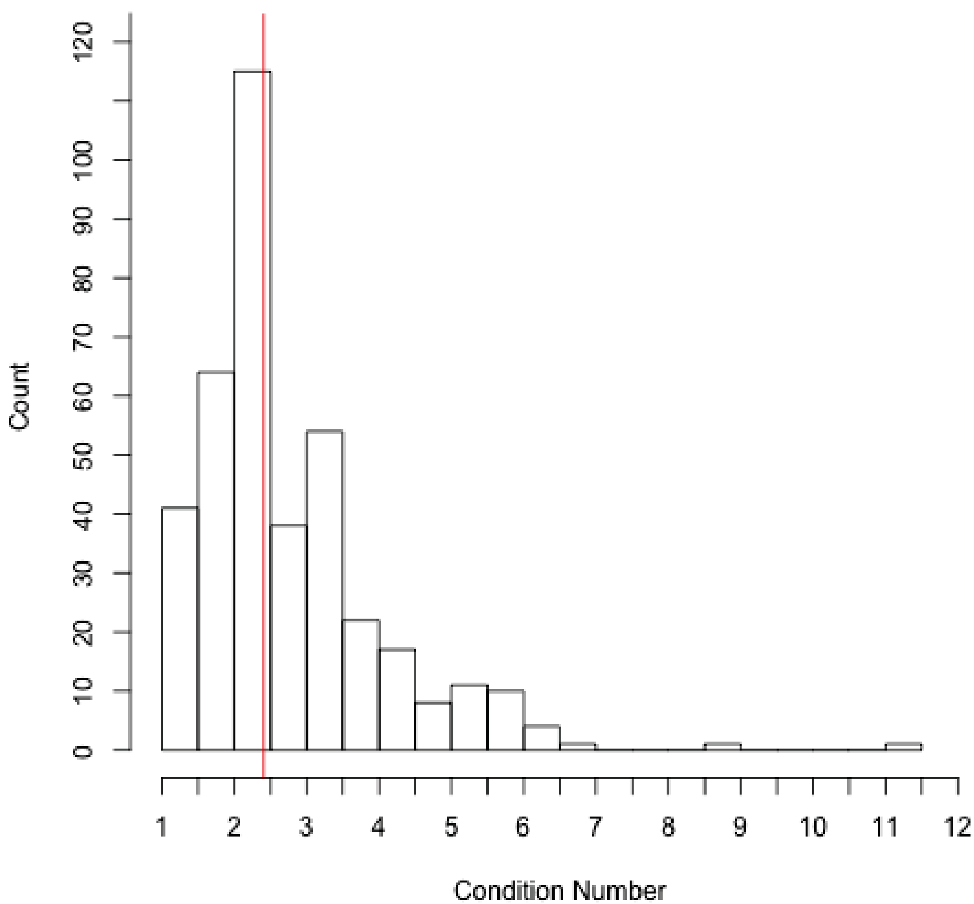
Histogram of the number of times each article included in the databased summary was cited as of February 24, 2017 according to google scholar. The red vertical line indicates the median (108) number of times articles were cited. Mean=223.20, s.d.=328.79, 1st quartile=51, 3rd quartile=248, N=197.

Figure 2: Distribution of Number of Times Each Article Was Cited as of February 24, 2017: Meta Analyses Only



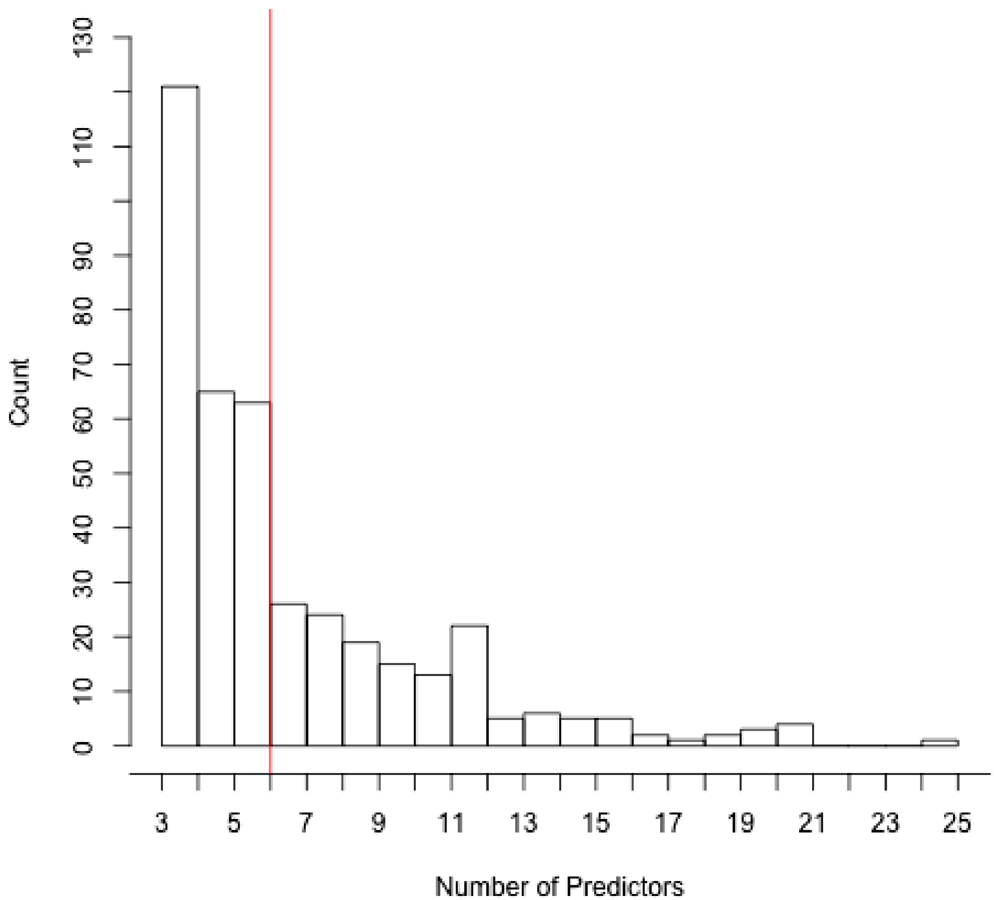
Histogram of the number of times each article included in the databased summary was cited as of February 24, 2017 according to google scholar. The red vertical line indicates the median (451) number of times articles were cited. Mean=510.60, s.d.=585.33, 1st quartile=180, 3rd quartile=570.20, N=20.

Figure 3: Distribution of κ from all Positive-Definite Predictor Correlation Matrices in the Database



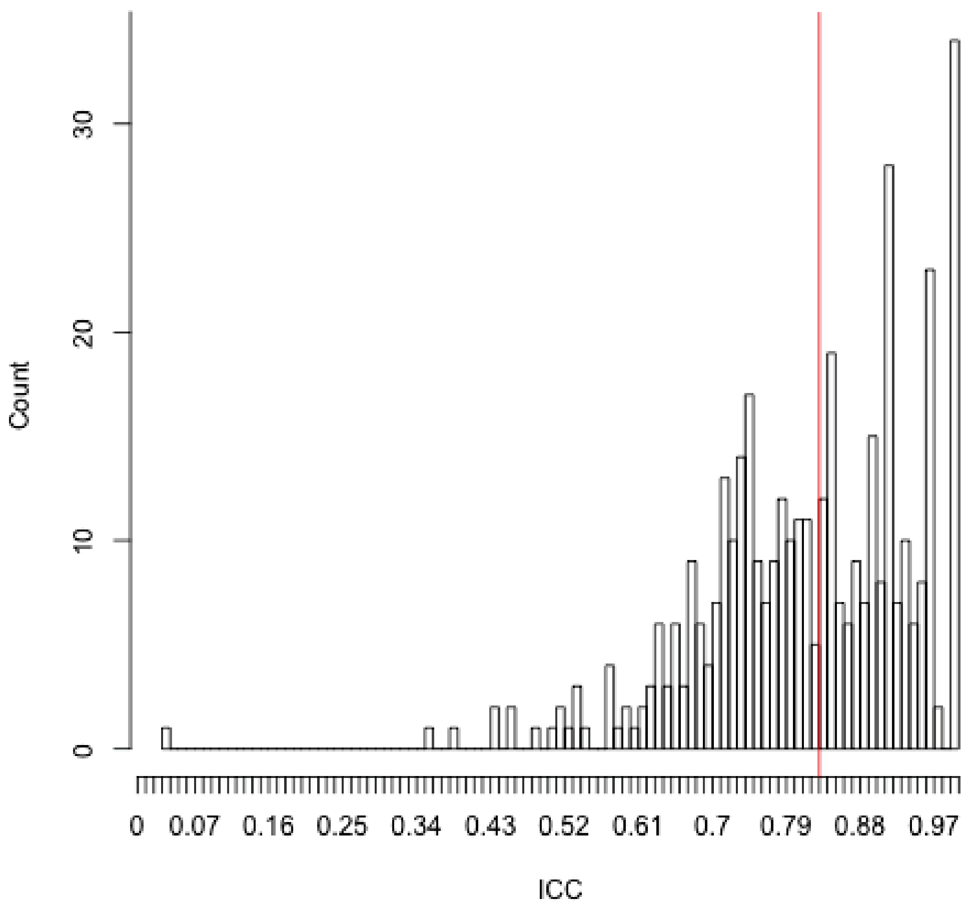
Histogram of κ from all positive definite $\boldsymbol{R_X}$ in the database of past literature. The red vertical line indicates the median (2.41). Mean=2.74, s.d.=1.27, 1st quartile=1.87, 3rd quartile=3.35, N=402.

Figure 4: Distribution of Number of Predictors for Regressions with Correlation Tables



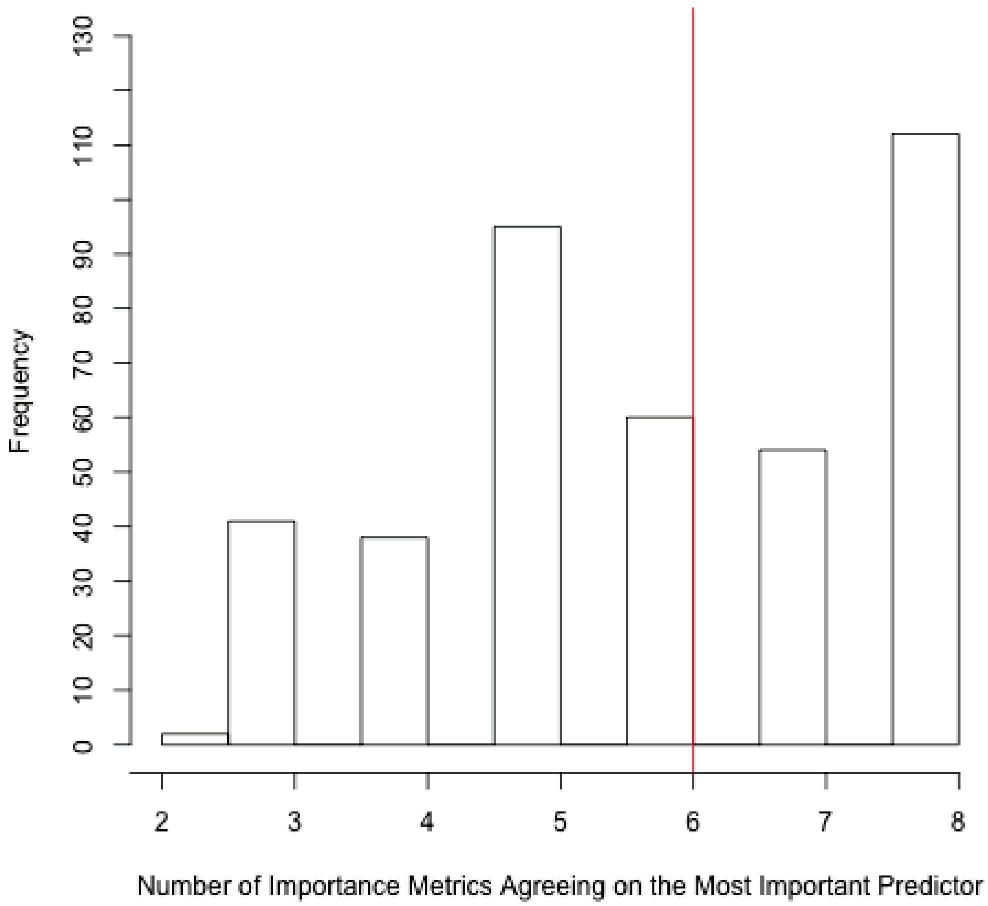
Histogram of the number of predictors for regressions from articles containing complete correlation tables. The red vertical line indicates the median (6) number of predictors. Mean=6.97, s.d.=3.92, 1st quartile=4, 3rd quartile=9, N=409.

Figure 5: Intraclass Correlations Among Ranks Produced by Relative Importance Analyses



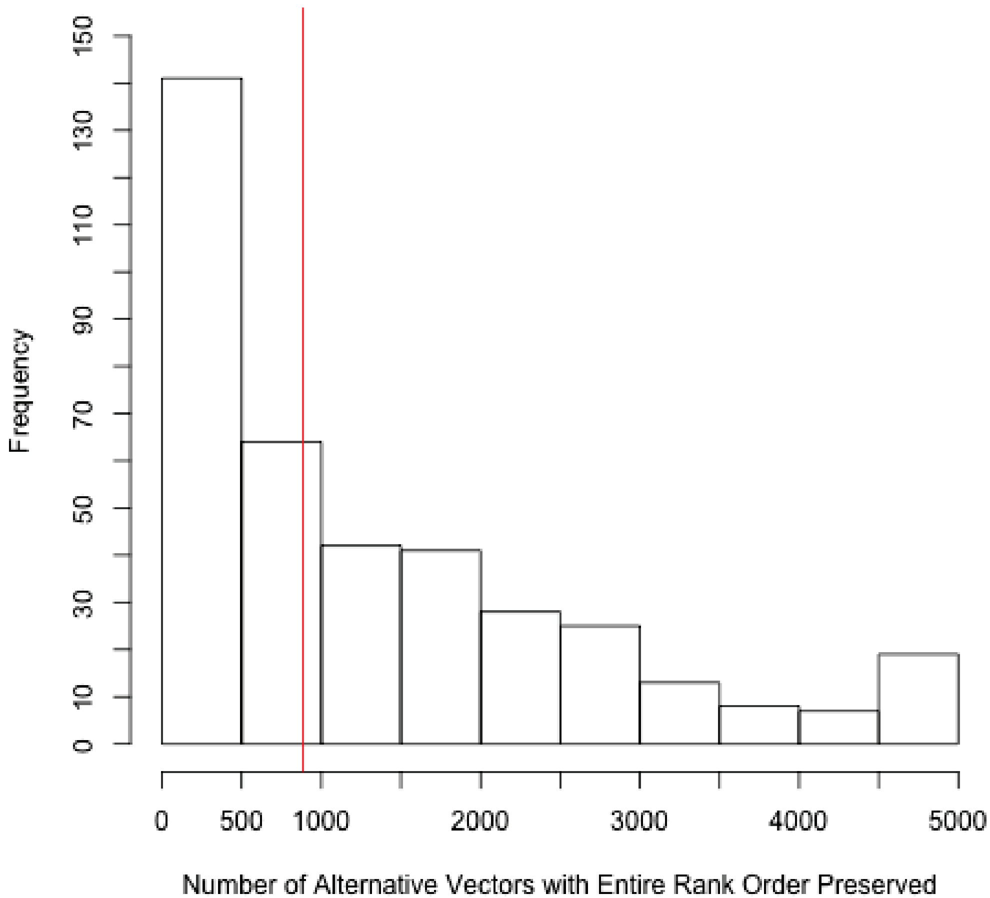
Histogram of the intraclass correlations among the ranks of the relative importance analyses used in this study for each regression examined. The red vertical line indicates the median (0.83). Mean=0.81, s.d.=0.13, 1st quartile=0.73, 3rd quartile=0.91, N=402.

Figure 6: Agreement Between Relative Importance Metrics Regarding the Most Important Predictor



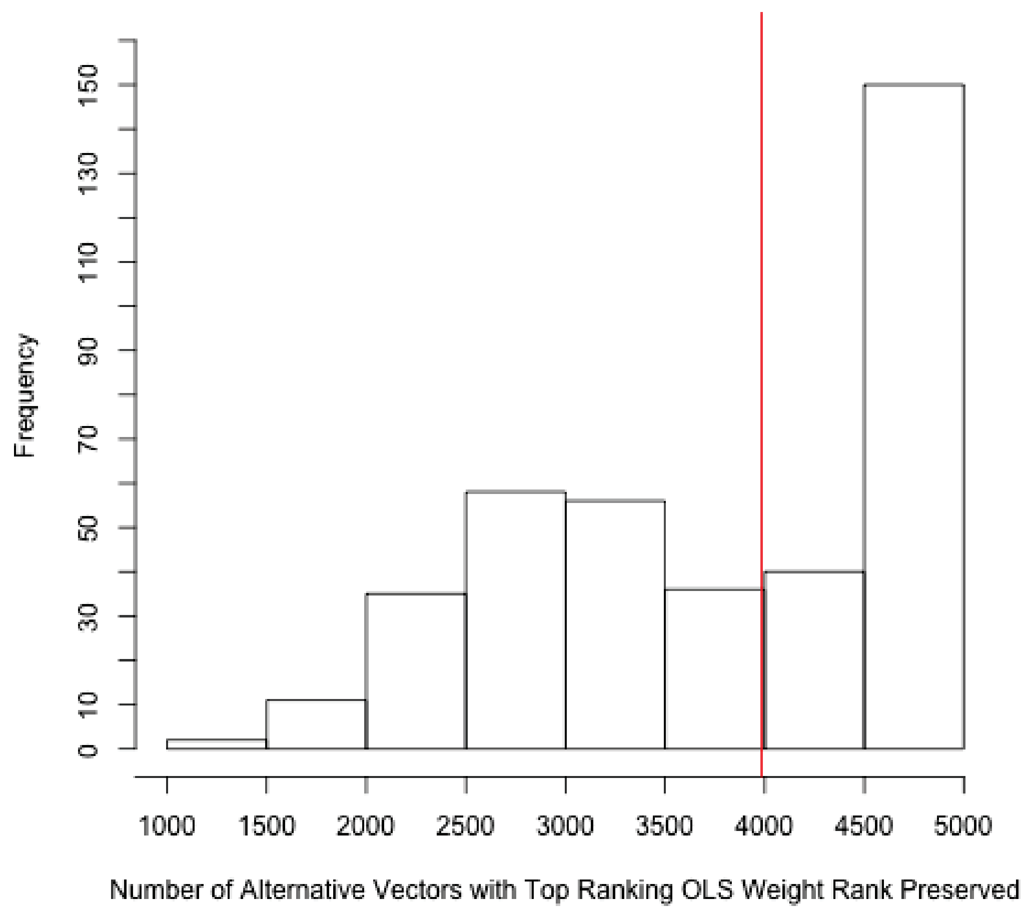
Histogram of number of relative importance metrics, out of the 8 metrics studied, agreed on the most important predictor in a regression. The red vertical line indicates the median (6). Mean=5.94, s.d.=1.69, 1st quartile=5, 3rd quartile=8, N=402.

Figure 7: Distribution Across Regressions of Number of Alternative Weight Vectors with Entire OLS Weight Rank Order Preserved for 0.01 Reduction in R^2



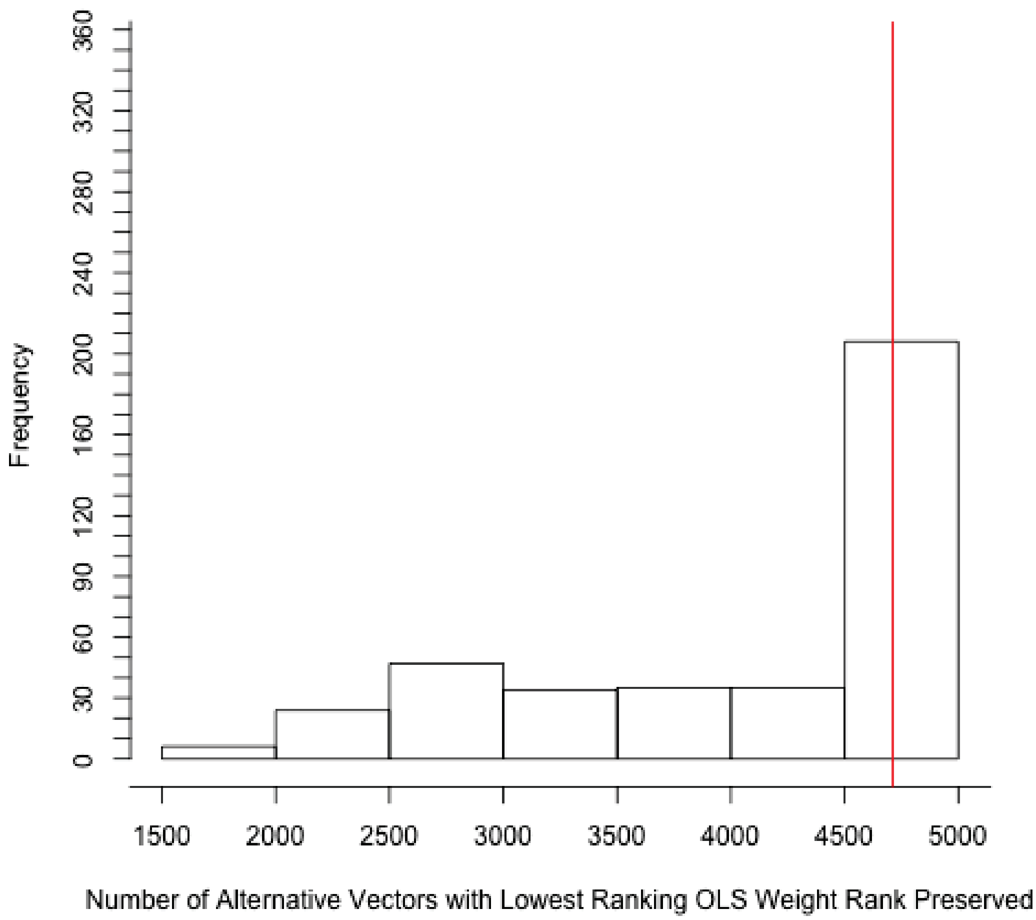
Histogram of number alternative weight vectors with the entire OLS weight vector rank order preserved from the fungible weights analysis. The red vertical line indicates the median (886.5). Mean=1330.89.51, s.d.=1361.67, 1st quartile=149.75, 3rd quartile=2060.00, N=387.

Figure 8: Distribution Across Regressions of Number of Alternative Weight Vectors with Top Ranking OLS Weight Rank Preserved for 0.01 Reduction in R^2



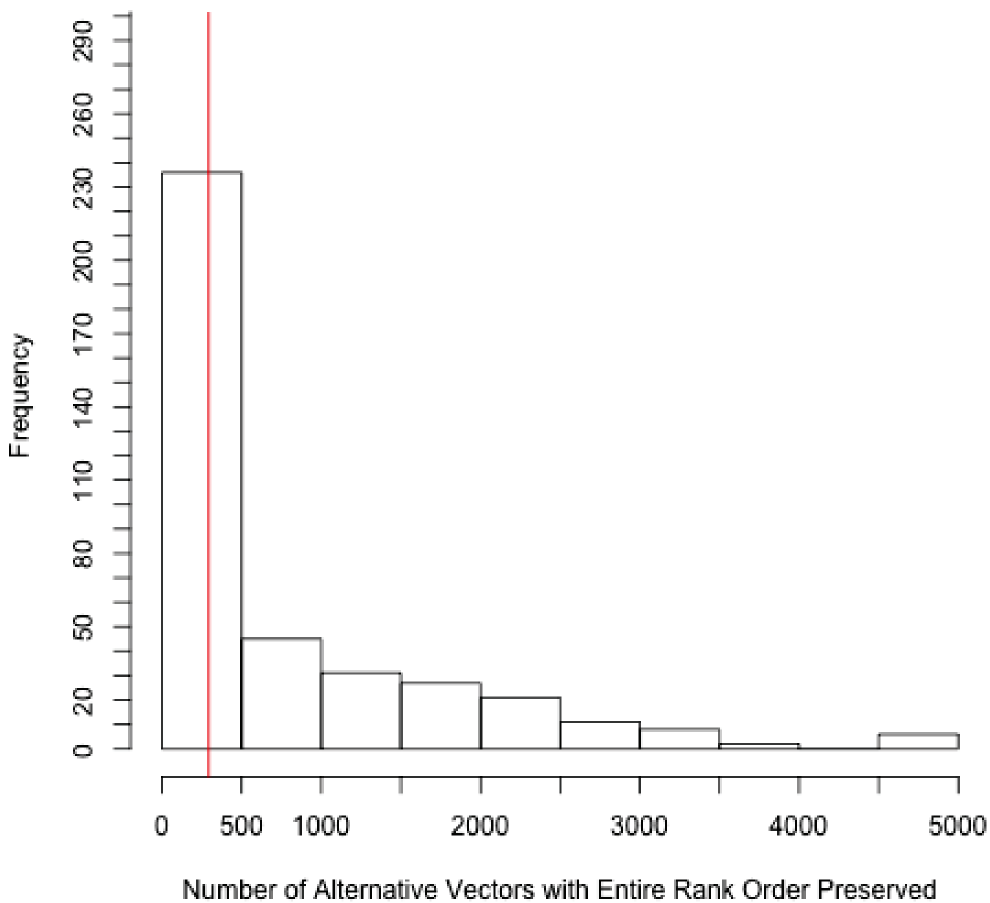
Histogram of number alternative weight vectors where the predictor associated with the top ranking OLS weight is also the predictor associated with the top ranking alternative weight from the fungible weights analysis. The red vertical line indicates the median (3986.00). Mean=3835.15, s.d.=1048.31, 1st quartile=2877.50, 3rd quartile=4991.00, N=387.

Figure 9: Distribution Across Regressions of Number of Alternative Weight Vectors with Lowest Ranking OLS Weight Rank Preserved for 0.01 Reduction in R^2



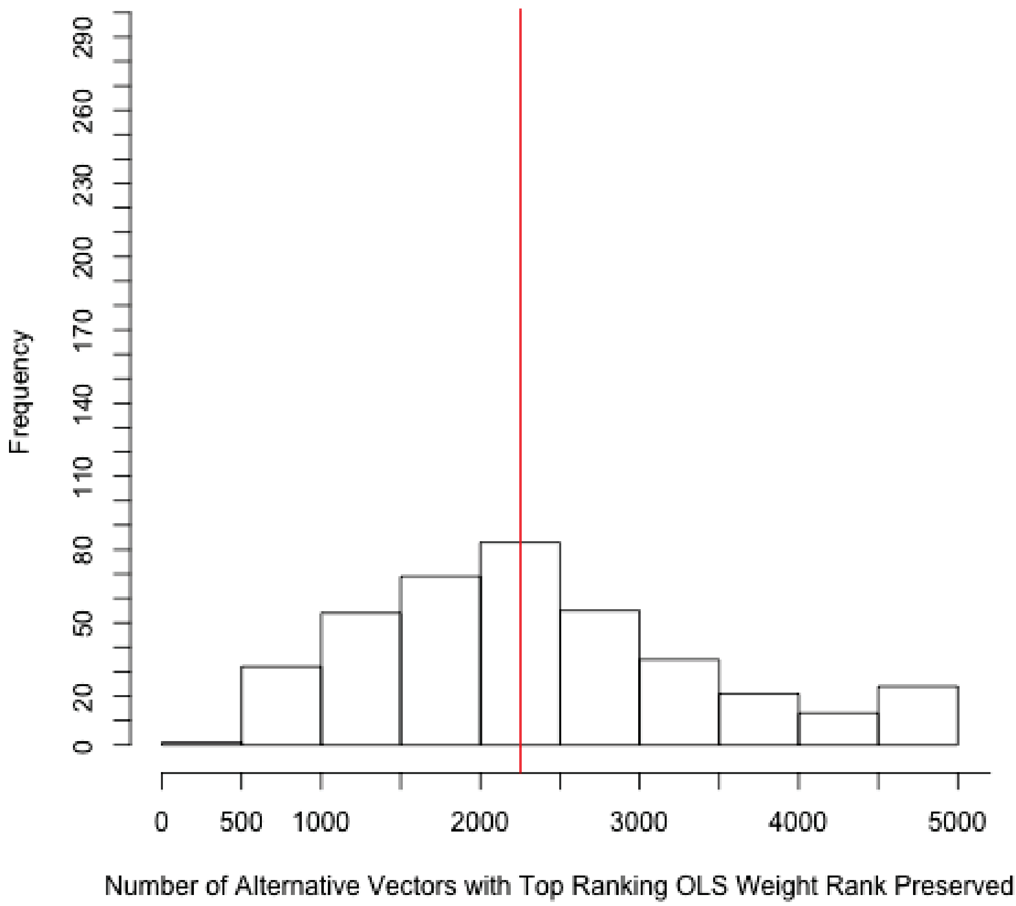
Histogram of number alternative weight vectors where the predictor associated with the lowest ranking OLS weight is also the predictor associated with the top ranking alternative weight from the fungible weights analysis. The red vertical line indicates the median (4712.00). Mean=4148.69, s.d.=988.77, 1st quartile=3241.50, 3rd quartile=5000.00, N=387.

Figure 10: Distribution Across Regressions of Number of Alternative Weight Vectors with Entire OLS Weight Rank Order Preserved When Using the Absolute Values of Weights for 0.01 Reduction in R^2



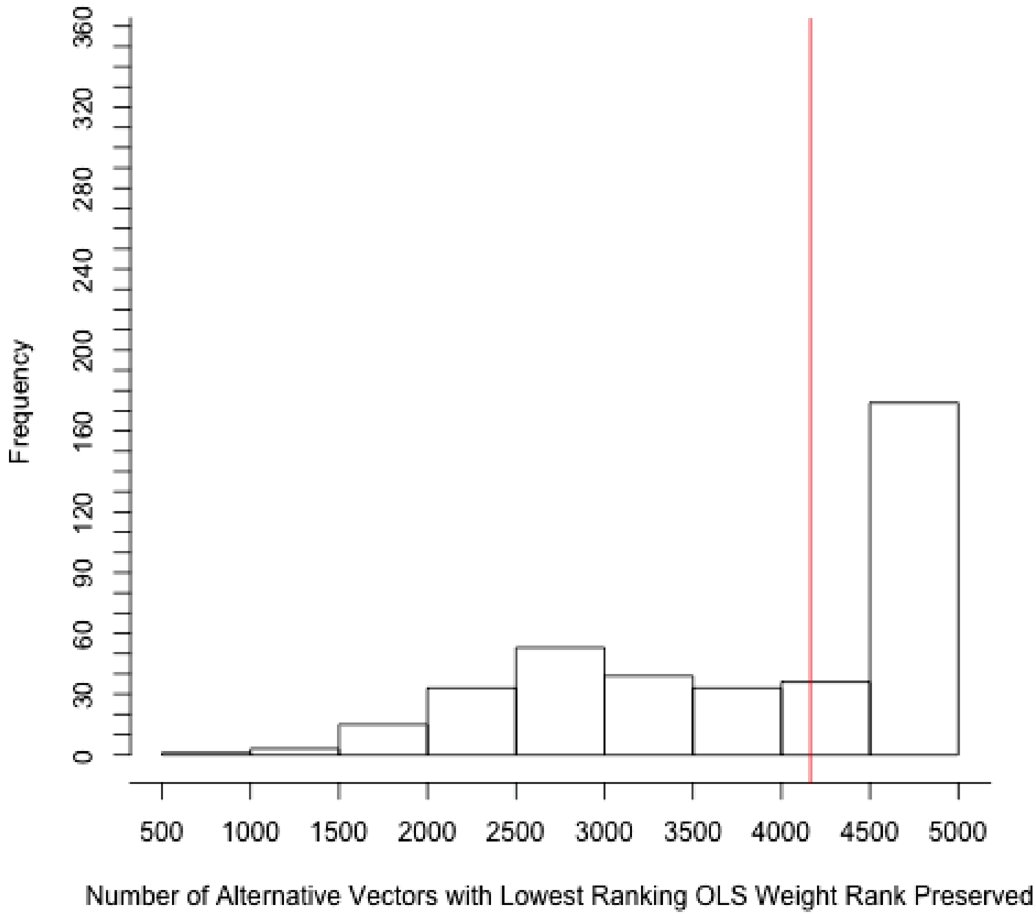
Histogram of number alternative weight vectors with the entire OLS weight vector rank order preserved from the fungible weights analysis when using the absolute values of weights. The red vertical line indicates the median (294.00). Mean=739.566, s.d.=1010.50, 1st quartile=17.50, 3rd quartile=1102.00, N=387.

Figure 11: Distribution Across Regressions of Number of Alternative Weight Vectors with Top Ranking OLS Weight Rank Preserved When Using the Absolute Values for 0.01 Reduction in R^2



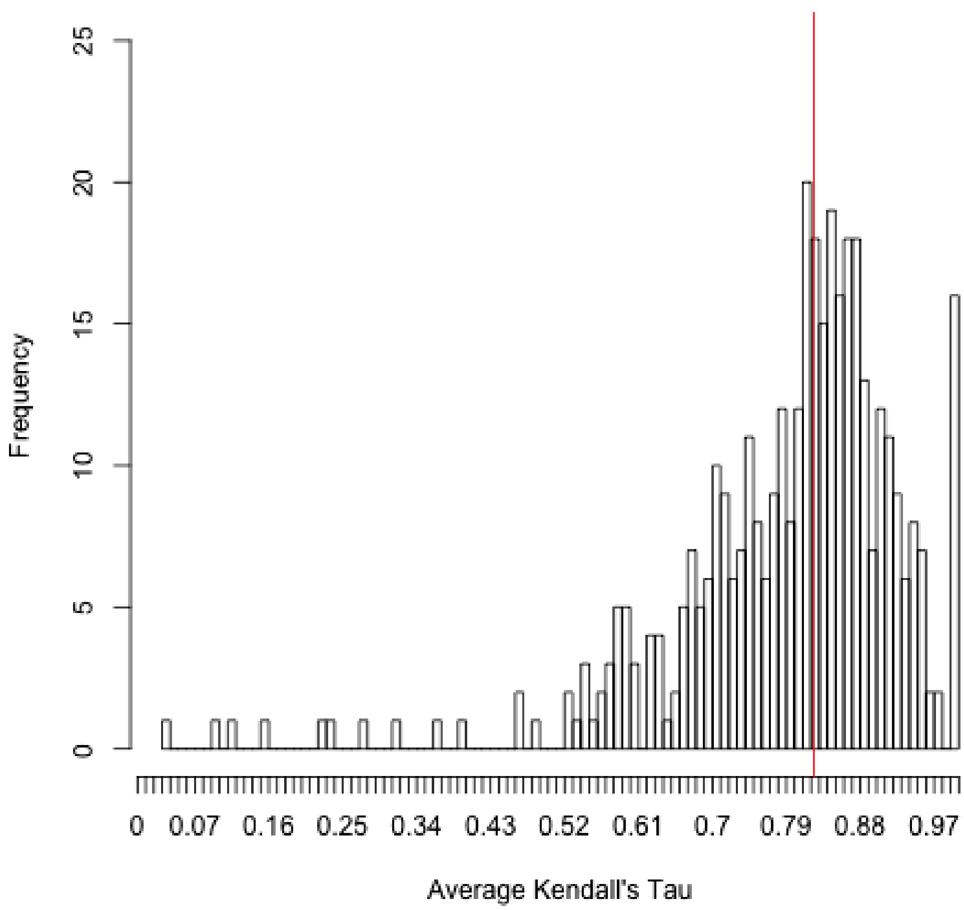
Histogram of number alternative weight vectors where the predictor associated with the top ranking OLS weight is also the predictor associated with the top ranking alternative weight from the fungible weights analysis when using the absolute values of weights. The red vertical line indicates the median (2254.00). Mean=2379.51, s.d.=1097.83, 1st quartile=1564.50, 3rd quartile=2930.50, N=387.

Figure 12: Distribution Across Regressions of Number of Alternative Weight Vectors with Lowest Ranking OLS Weight Rank Preserved When Using the Absolute Values for 0.01 Reduction in R^2



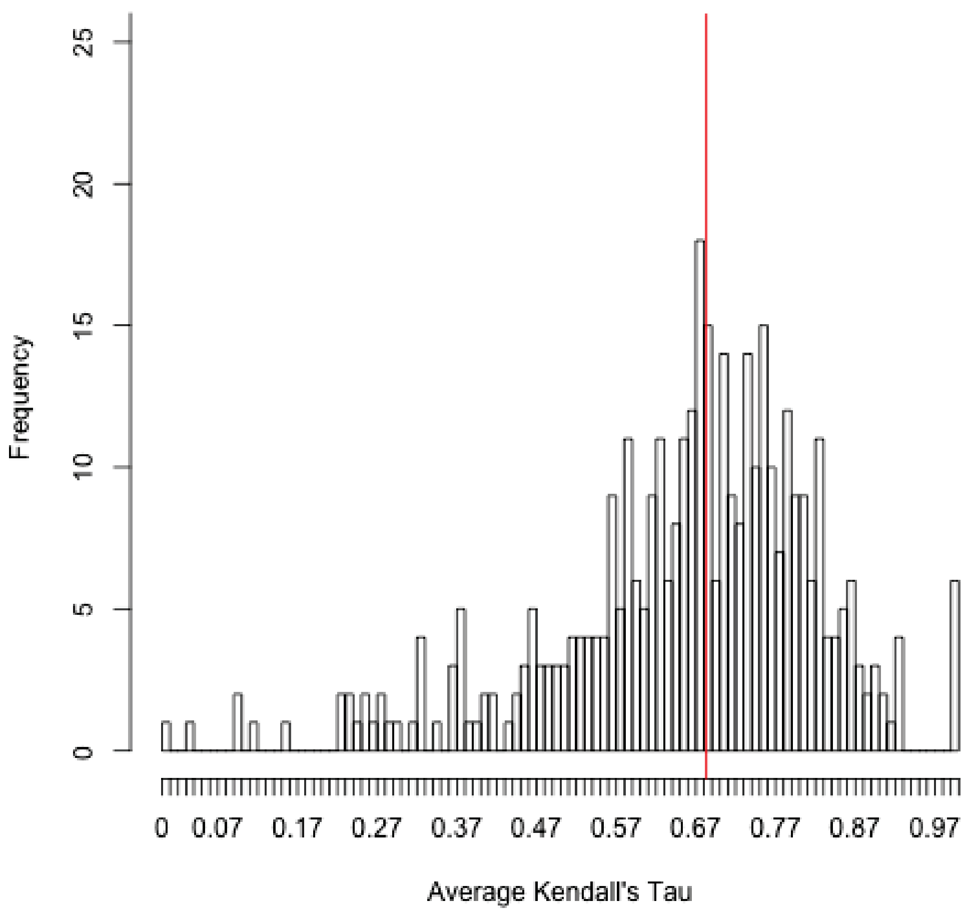
Histogram of number alternative weight vectors where the predictor associated with the lowest ranking OLS weight is also the predictor associated with the top ranking alternative weight from the fungible weights analysis when using the absolute values of weights. The red vertical line indicates the median (4164.00). Mean=3919.80, s.d.=1104.32, 1st quartile=2879.00, 3rd quartile=5000.00, N=387.

Figure 13: Average Kendall's τ Between Predictor Ranks for OLS and Alternative Weight Vectors for 0.01 Reduction in R^2



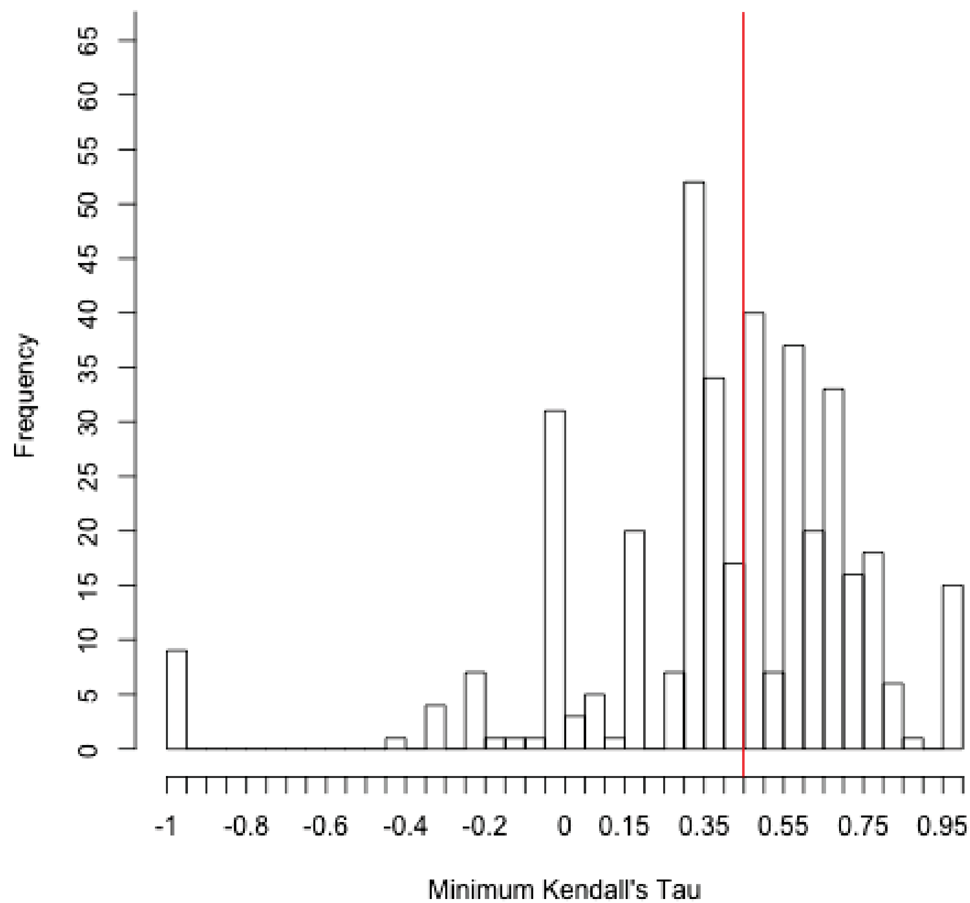
Histogram of average kendall's τ between predictor ranks for OLS and alternative rank vectors. The red vertical line indicates the median (0.82). Mean=0.79, s.d.=0.14, 1st quartile=0.73, 3rd quartile=0.88, N=387.

Figure 14: Average Kendall's τ Between Predictor Ranks for OLS and Alternative Weight Vectors When Absolute Values of Weights are Used for 0.01 Reduction in R^2



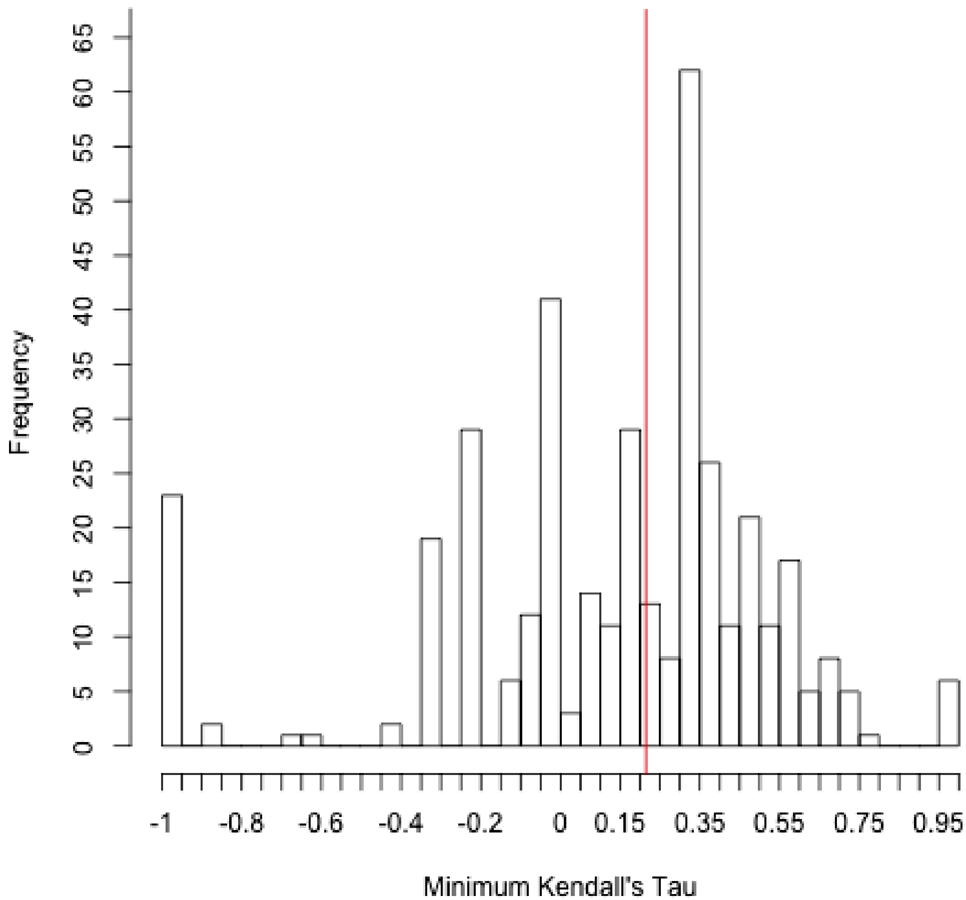
Histogram of average kendall's τ between predictor ranks for OLS and alternative rank vectors when absolute values of weights are used. The red vertical line indicates the median (0.68). Mean=0.66, s.d.=0.17, 1st quartile=0.58, 3rd quartile=0.77, N=387.

Figure 15: Minimum Kendall's τ Between Predictor Ranks for OLS and Alternative Weight Vectors for 0.01 Reduction in R^2



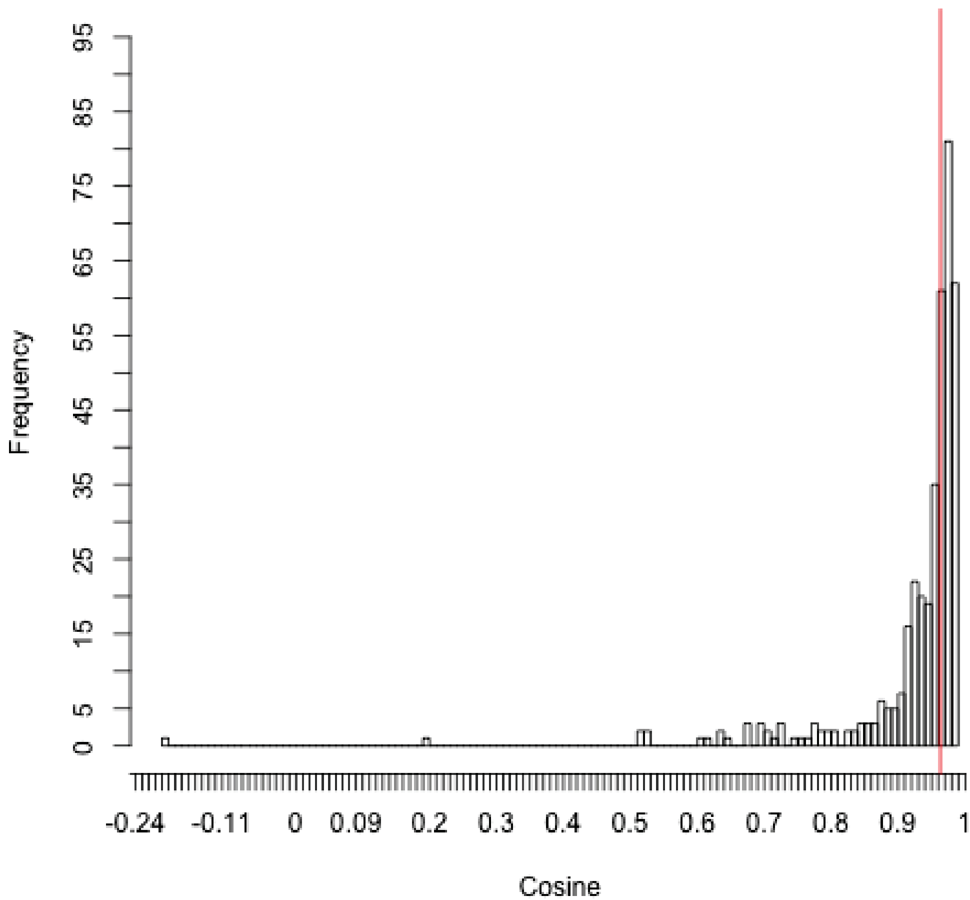
Histogram of minimum kendall's τ between predictor ranks for OLS and alternative rank vectors. The red vertical line indicates the median (0.45). Mean=0.41, s.d.=0.35, 1st quartile=0.33, 3rd quartile=0.62, N=387.

Figure 16: Minimum Kendall's τ Between Predictor Ranks for OLS and Alternative Weight Vectors When Absolute Values of Weights are Used for 0.01 Reduction in R^2



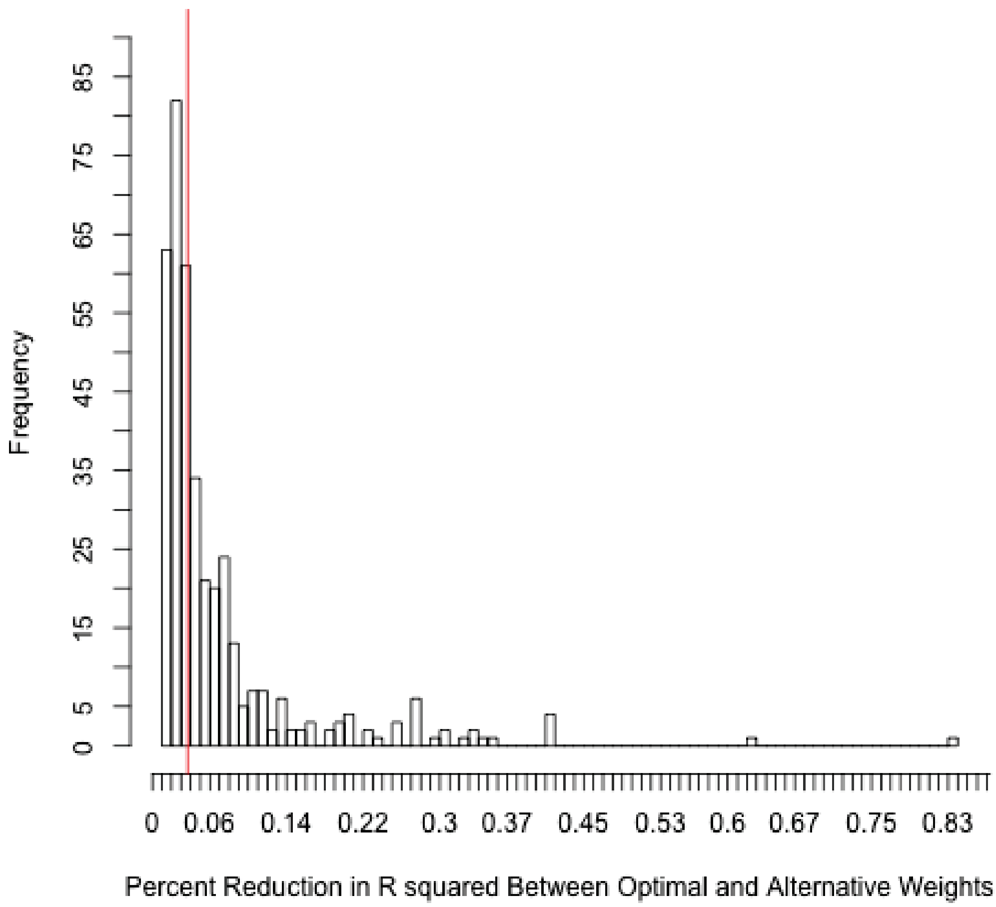
Histogram of minimum kendall's τ between predictor ranks for OLS and alternative rank vectors when absolute values of weights are used. The red vertical line indicates the median (0.21). Mean=0.14, s.d.=0.41, 1st quartile=0.00, 3rd quartile=0.40, N=387.

Figure 17: Distribution of $cos\measuredangle \boldsymbol{k}_i O \boldsymbol{k}_j$



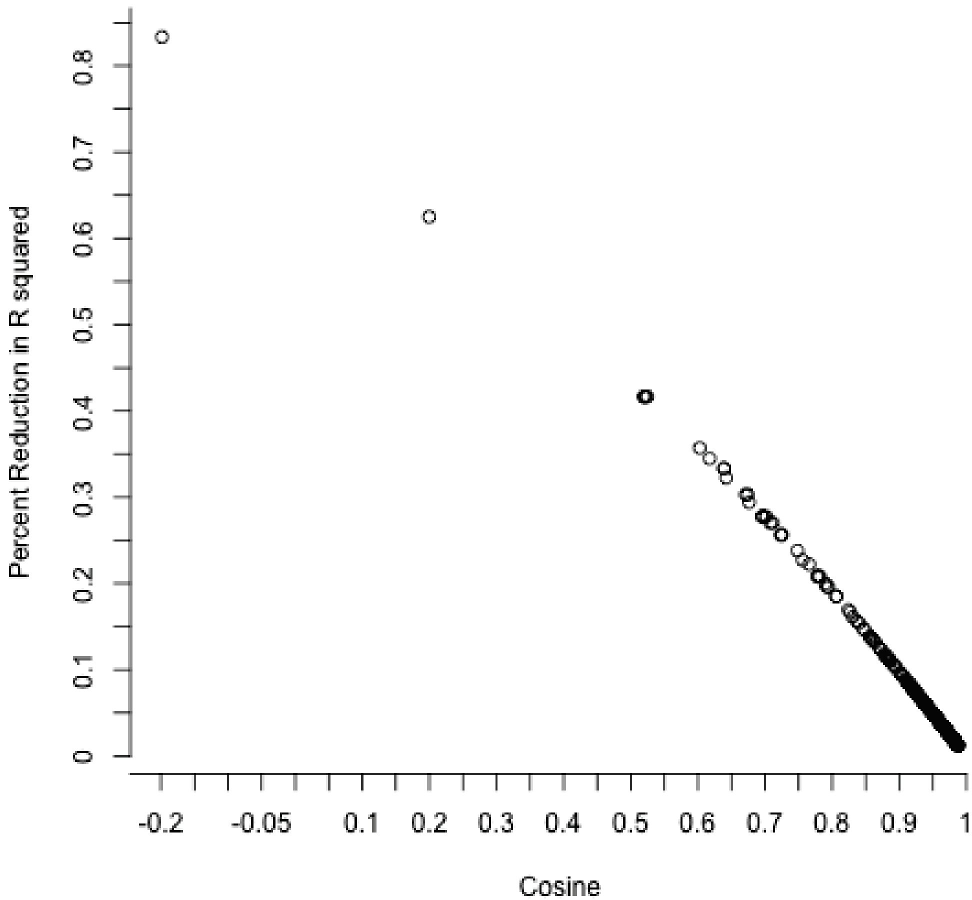
Histogram of $cos\measuredangle \boldsymbol{k}_i O \boldsymbol{k}_j$. The red vertical line indicates the median (0.96). Mean=0.93, s.d.=0.11, 1st quartile=0.92, 3rd quartile=0.98, N=387.

Figure 18: Percent Reduction of R^2 Between Optimal and Alternative Models When Reducing R^2 by 0.01



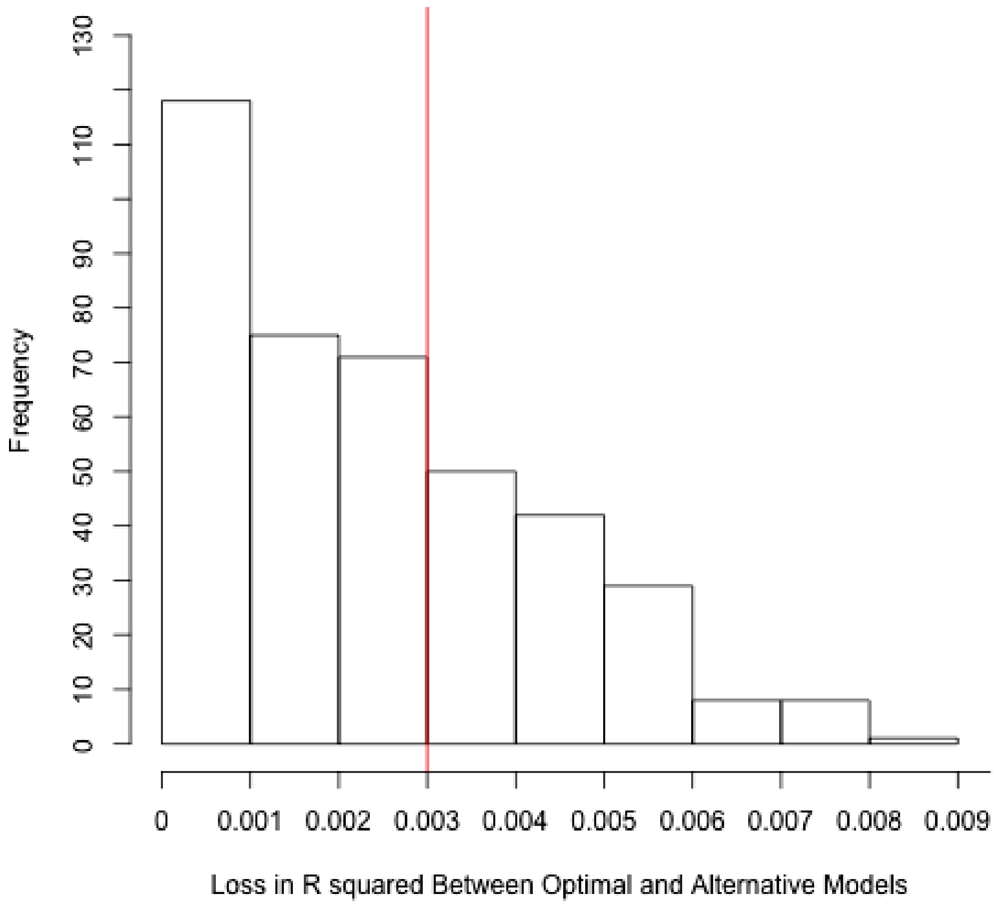
Histogram of the percent reduction R^2 between optimal and Alternative Models When Reducing R^2 by 0.01 using fungible weights. The red vertical line indicates the median (3.68%). Mean=6.93%, s.d.=8.89%, 1st quartile=2.38%, 3rd quartile=7.58%, N=387.

Figure 19: $cos\measuredangle \boldsymbol{k}_i O \boldsymbol{k}_j$ and Percent Reduction of R^2 Between Optimal and Alternative Models When Reducing R^2 by 0.01



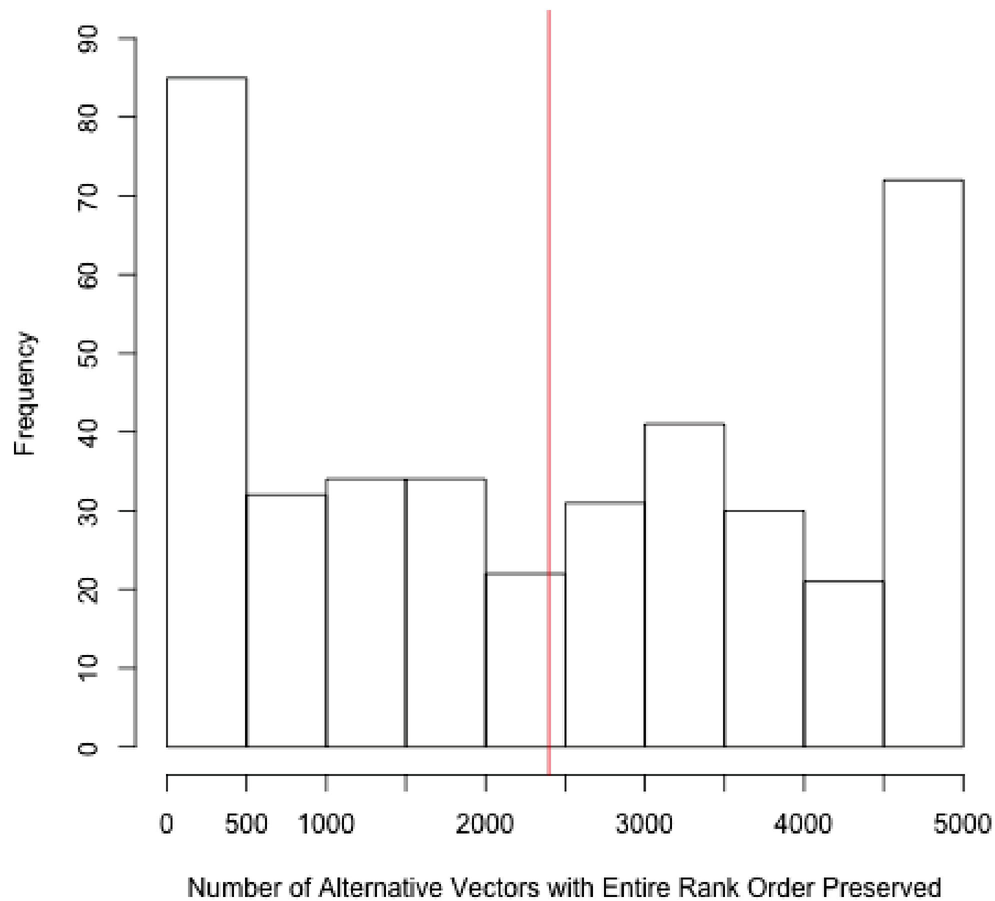
Scatterplot of the relationship between $cos\measuredangle \boldsymbol{k}_i O \boldsymbol{k}_j$ and the percent reduction in R^2 between optimal and alternative models when the R^2 from the OLS model is reduced by a constant of 0.01.

Figure 20: Absolute Reduction in Model R^2 Between Optimal and Alternative Models for 1% Reduction in Optimal R^2



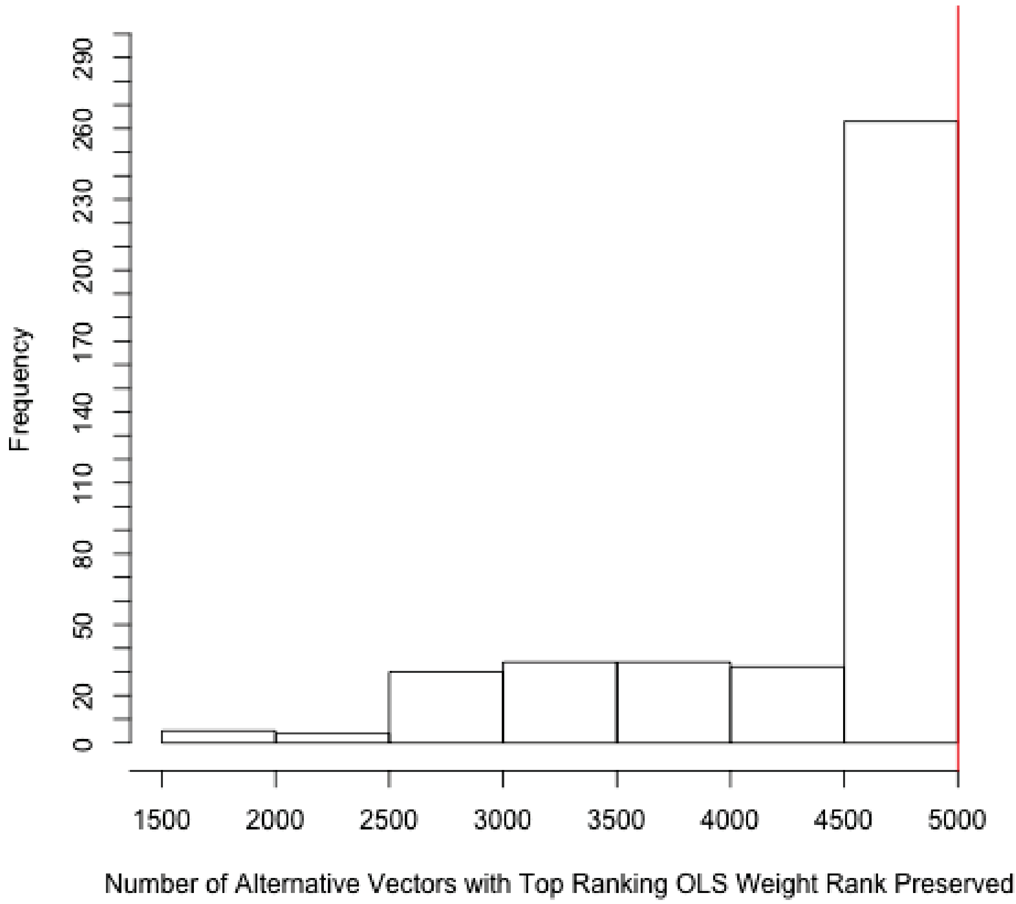
Histogram of absolute reduction in model R^2 between optimal and alternative models where the optimal R^2 was reduced by 1%. The red vertical line indicates the median (0.003). Mean=0.003, s.d.=0.002, 1st quartile=0.001, 3rd quartile=0.001, N=402.

Figure 21: Distribution Across Regressions of Number of Alternative Weight Vectors with Entire OLS Weight Rank Order Preserved for 1% Reduction in R^2



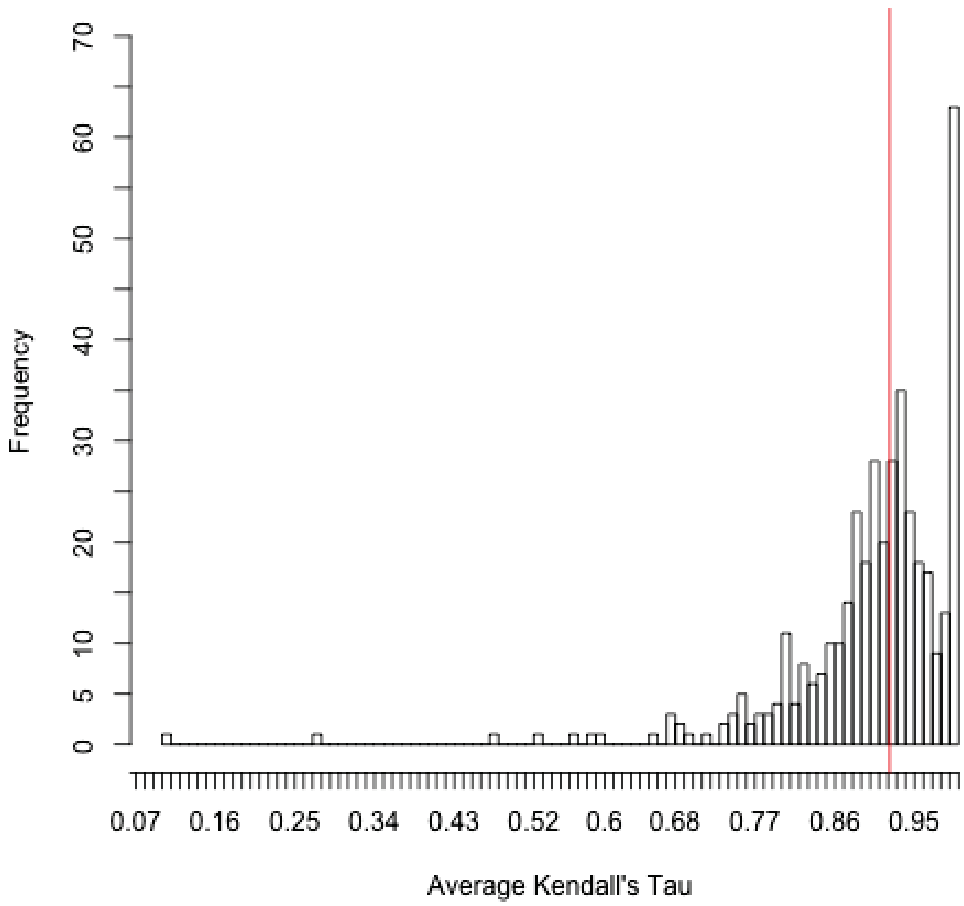
Histogram of number alternative weight vectors with the entire OLS weight vector rank order preserved from the fungible weights analysis where the model R^2 was reduced by 1% in the alternative models. The red vertical line indicates the median (2398.50). Mean=2399.25, s.d.=1729.55, 1st quartile=843.25, 3rd quartile=3875.00, N=402.

Figure 22: Distribution Across Regressions of Number of Alternative Weight Vectors with top Ranking OLS Weight Rank Preserved for 1% Reduction in R^2



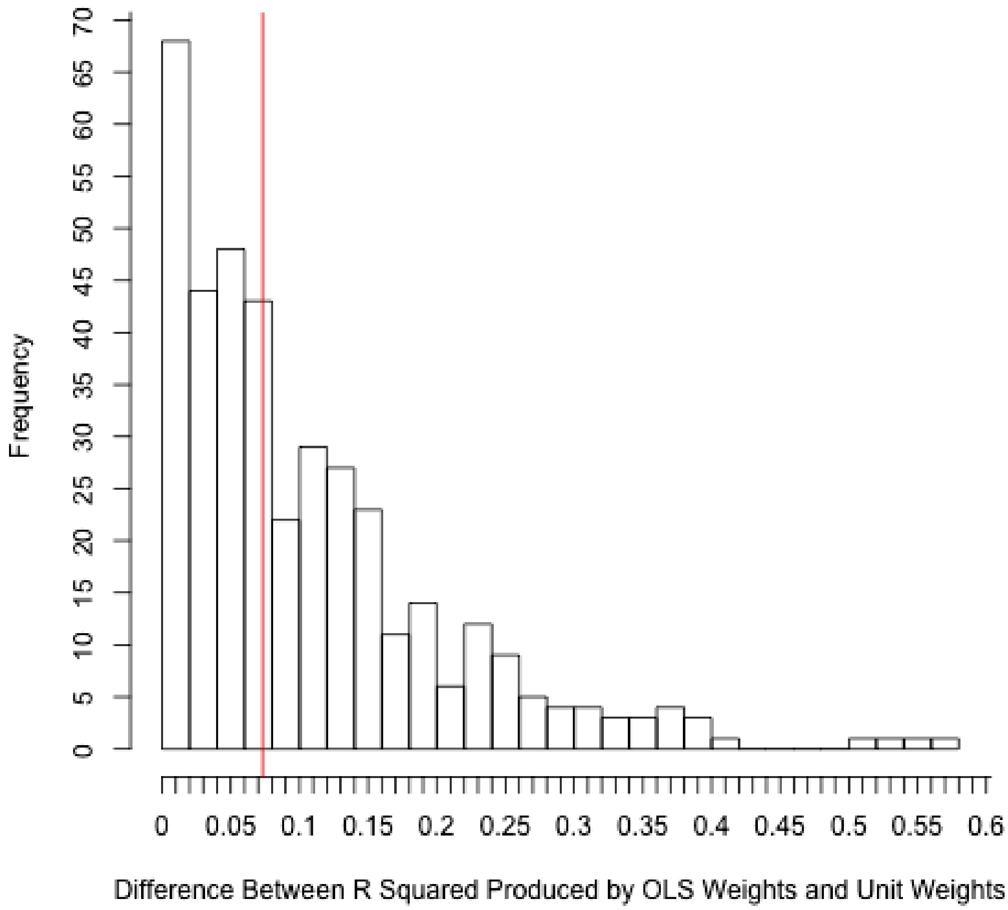
Histogram of number alternative weight vectors where the predictor associated with the top ranking OLS weight is also the predictor associated with the top ranking alternative weight from the fungible weights analysis where the model R^2 was reduced by 1% in the alternative models. The red vertical line indicates the median (5000). Mean=4425.55, s.d.=839.90, 1st quartile=3911.75, 3rd quartile=5000, N=402.

Figure 23: Average Kendall's τ Between Predictor Ranks for OLS and Alternative Weight Vectors for 1% Reduction in R^2



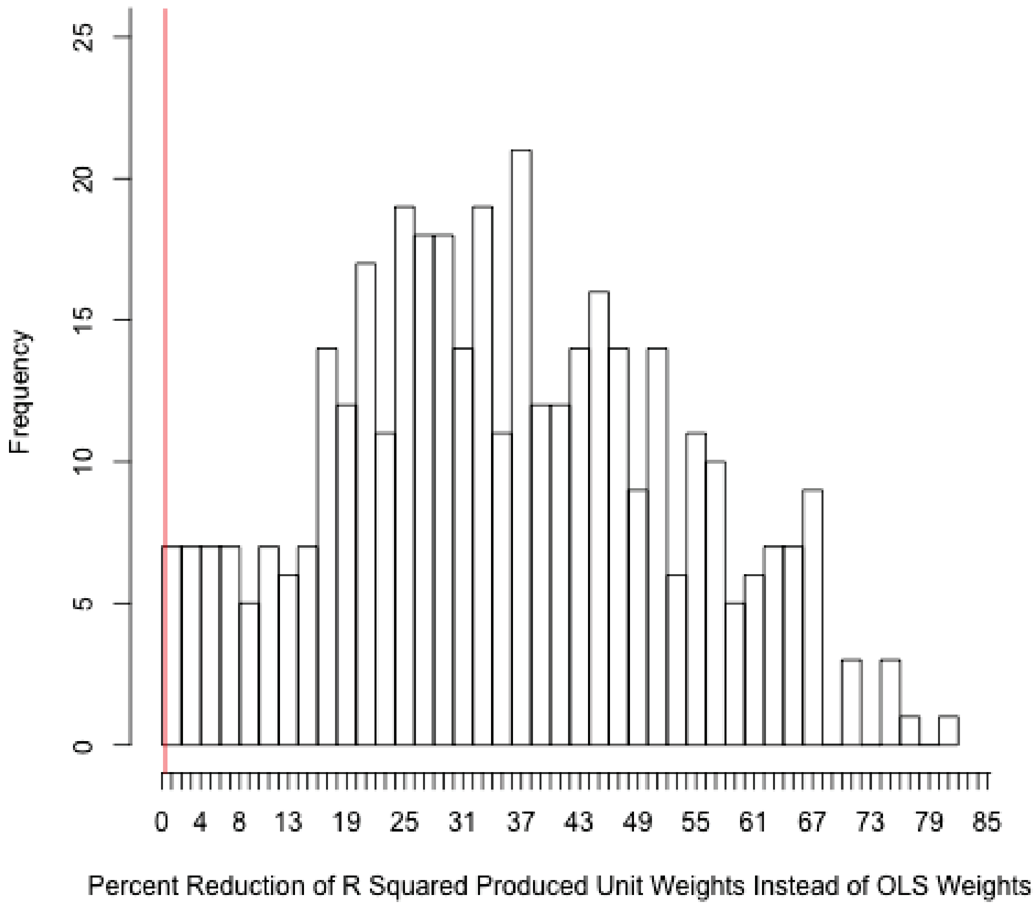
Histogram of average kendall's τbetween predictor ranks for OLS and alternative rank vectors fungible weights analysis where the model R^2 was reduced by 1% in the alternative models. The red vertical line indicates the median (0.92). Mean=0.90, s.d.=0.10, 1st quartile=0.88, 3rd quartile=0.96, N=402.

Figure 24: Raw Difference between R^2 for Models with OLS and Unit Weights



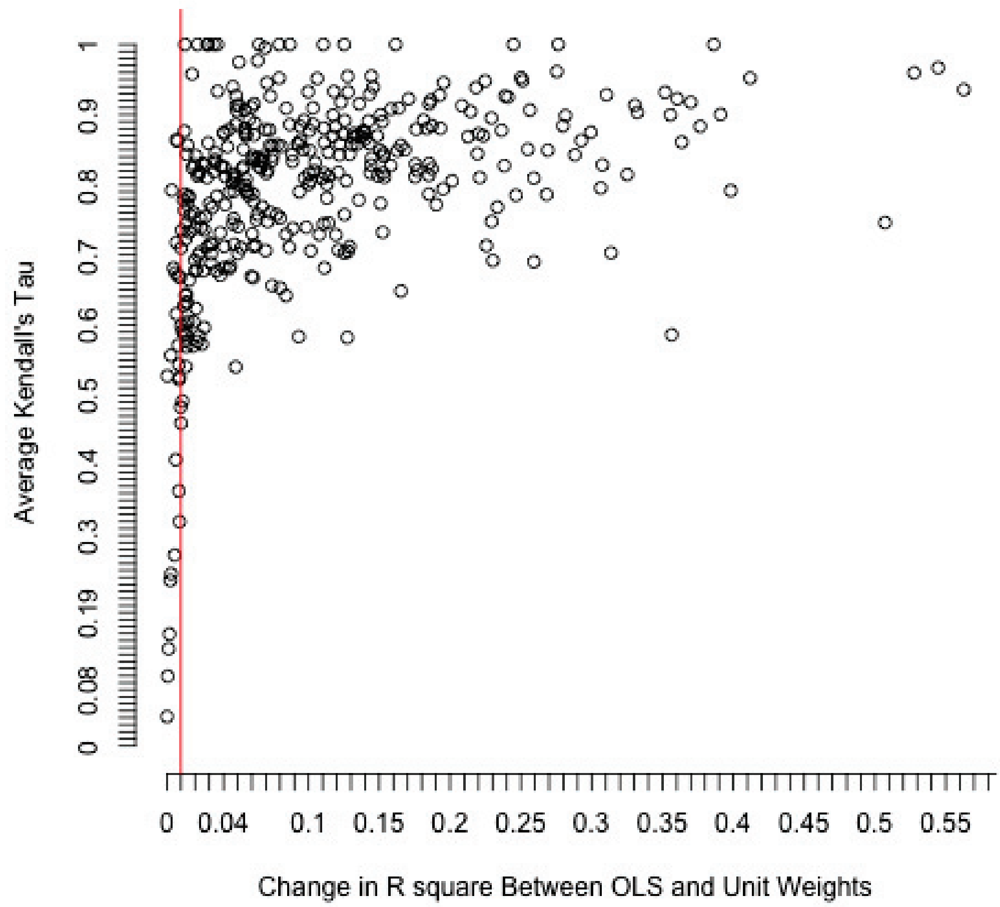
Histogram of the difference between the model R^2 for models with optimal weights and the model R^2 for models with unit weights. The red vertical line indicates the median (0.07). Mean=0.11, s.d.=0.10, 1st quartile=0.03, 3rd quartile=0.15, N=402.

Figure 25: Percent Difference between R^2 for Models with OLS and Unit Weights



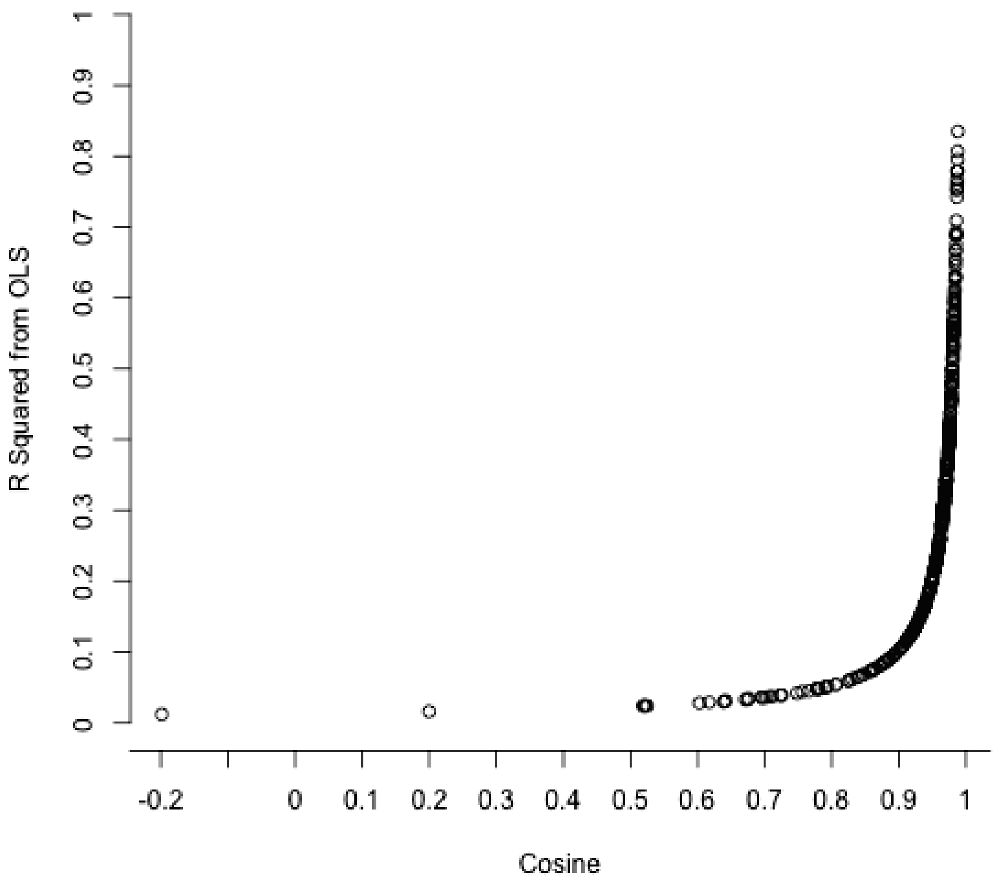
Histogram of the percent difference between the model R^2 for models with optimal weights and the model R^2 for models with unit weights. The red vertical line indicates the median (33.86%). Mean=34.95%, s.d.=17.57%, 1st quartile=22.31%, 3rd quartile=47.01%, N=402.

Figure 26: Relationship Between Change in R^2 Between Unit and OLS Weighted Models and the Average Kendall's τ



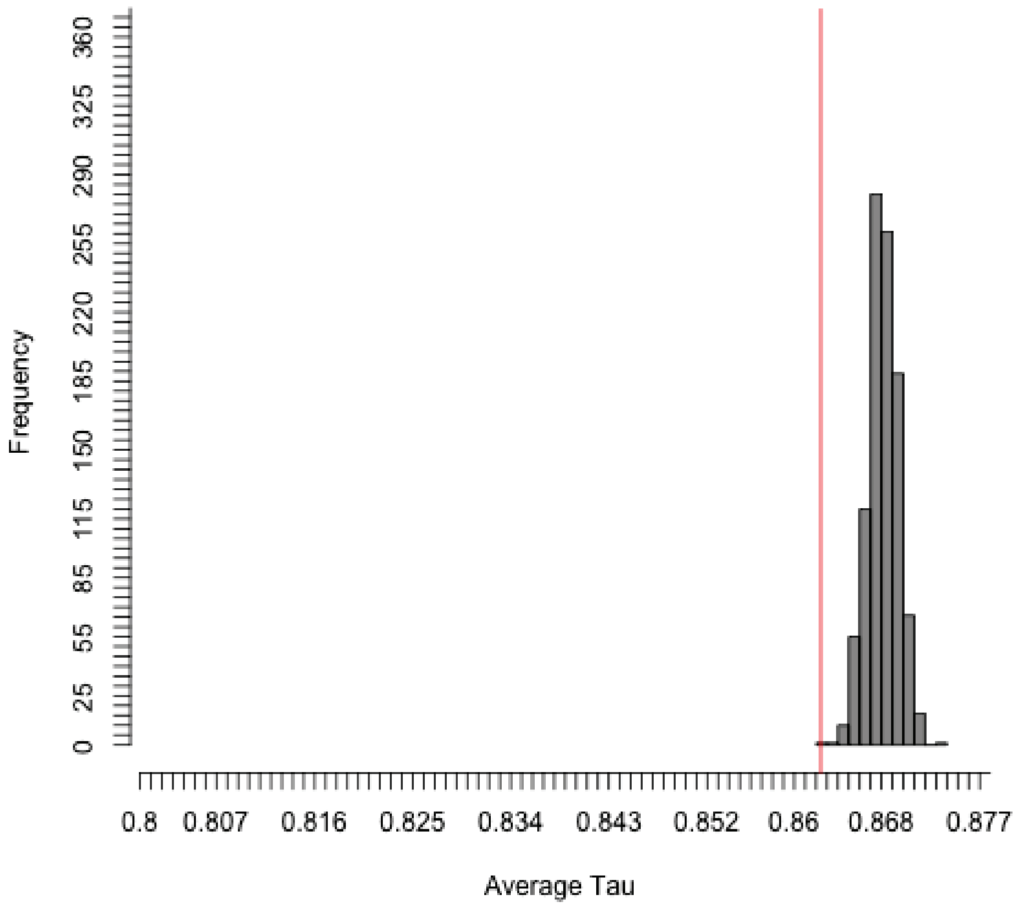
Scatterplot of the change in R^2 between models using linear weights and models using OLS weights and the average kendall's τ. The red vertical line is placed at 0.01, the reduction in R^2 between the OLS and alternative models in the fungible weights analysis that produced the Kendall's τ in the plot.

Figure 27: Relationship Between R^2 and $cos\measuredangle \boldsymbol{k_i} O \boldsymbol{k_j}$



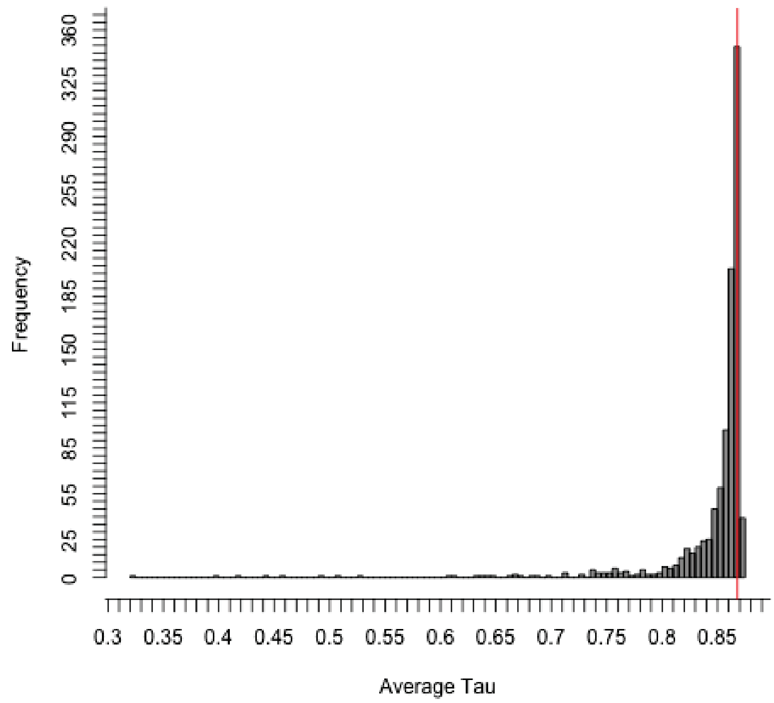
Relationship between the OLS model R^2 and $cos\measuredangle \boldsymbol{k_i} O \boldsymbol{k_j}$ for alternative models where the R^2 from the OLS model is reduced by a constant of 0.01.

Figure 28: Fungible Weights Distribution of Average τ for Mumford et al. (2008)



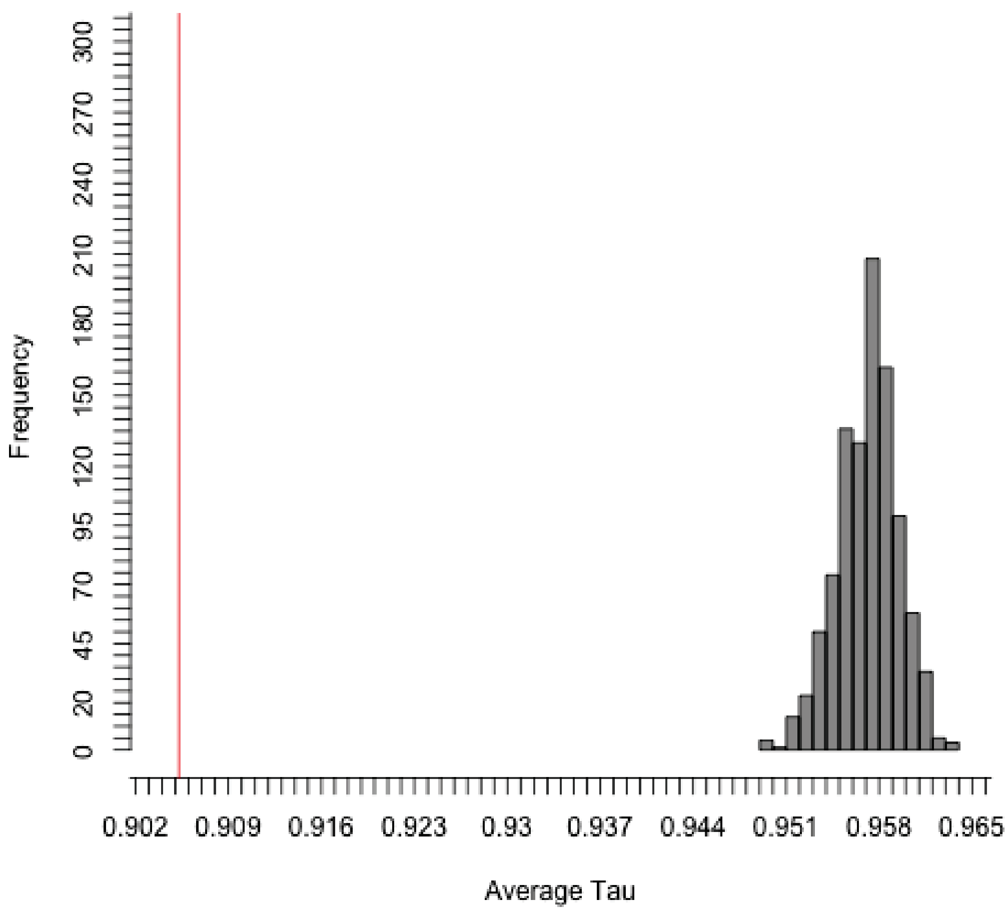
Histogram of average kendall's τ between predictor ranks for OLS and alternative rank vectors for the regression taken from Mumford et al. (2008). In the alternative models the R^2 from the OLS model is reduced by a constant of 0.01. N=1000 average kendall's τ, where each average is computed from 5000 alternative weight vectors generated with the fungible weights procedure. The red line represents the median (0.862) of the average kendall's τ for the 1000 average kendall's τ's computed using predictor matrices generated by Fungible R and put through the same fungible weights procedure as the original regression. Mean=0.868, median = 0.868, s.d.=0.001, 1st quartile=0.867, 3rd quartile=0.869.

Figure 29: Fungible R Distribution of Average τ for Mumford et al. (2008)



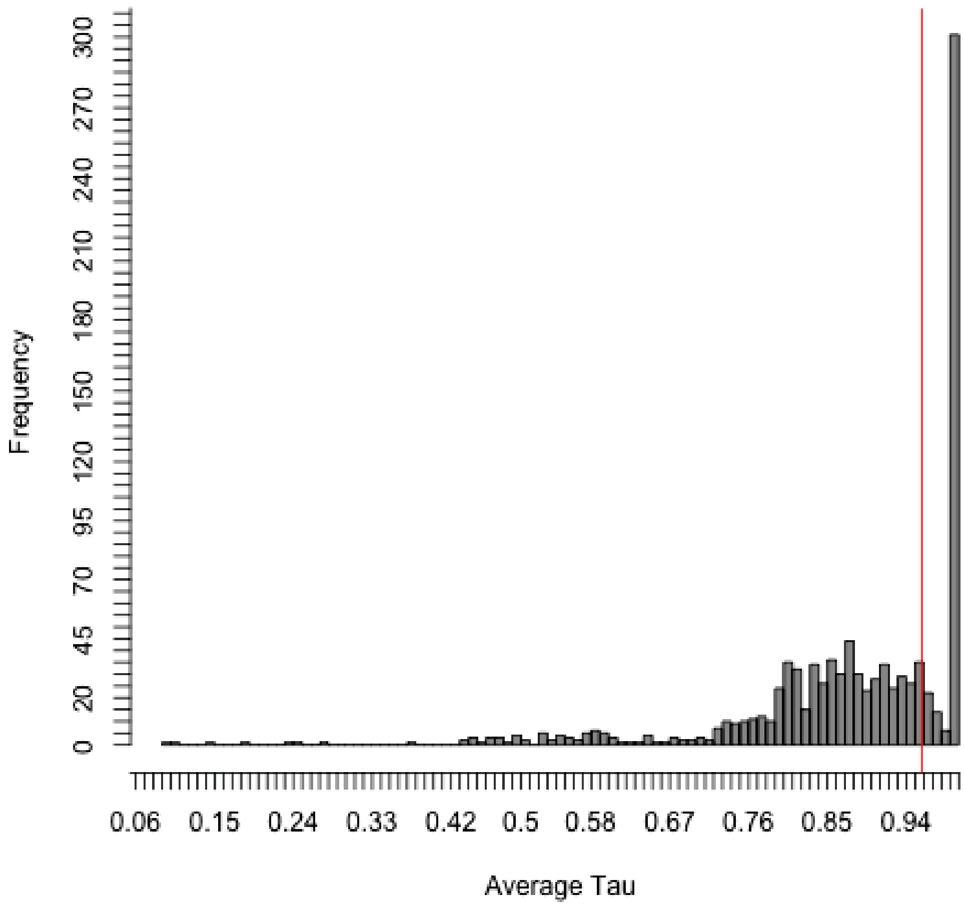
Histogram of average kendall's τ between predictor ranks for OLS and alternative rank vectors for regressions computed using predictor matrices generated by Fungible R using the original correlation and regression information from Mumford et al. (2008). In the alternative models the R^2 from the OLS model is reduced by a constant of 0.01. N=1000 average kendall's τ, where each average is computed from 5000 alternative weight vectors generated with the fungible weights procedure. The red line represents the median (0.868) of the average kendall's τ for the 1000 average kendall's τ's computed using the original predictor correlation matrices and put through the same fungible weights procedure described above. Mean=0.847, median = 0.862, s.d.=0.050, 1st quartile=0.850, 3rd quartile=0.867.

Figure 30: Fungible Weights Distribution of Average τ for Dabos & Rousseau(2004)



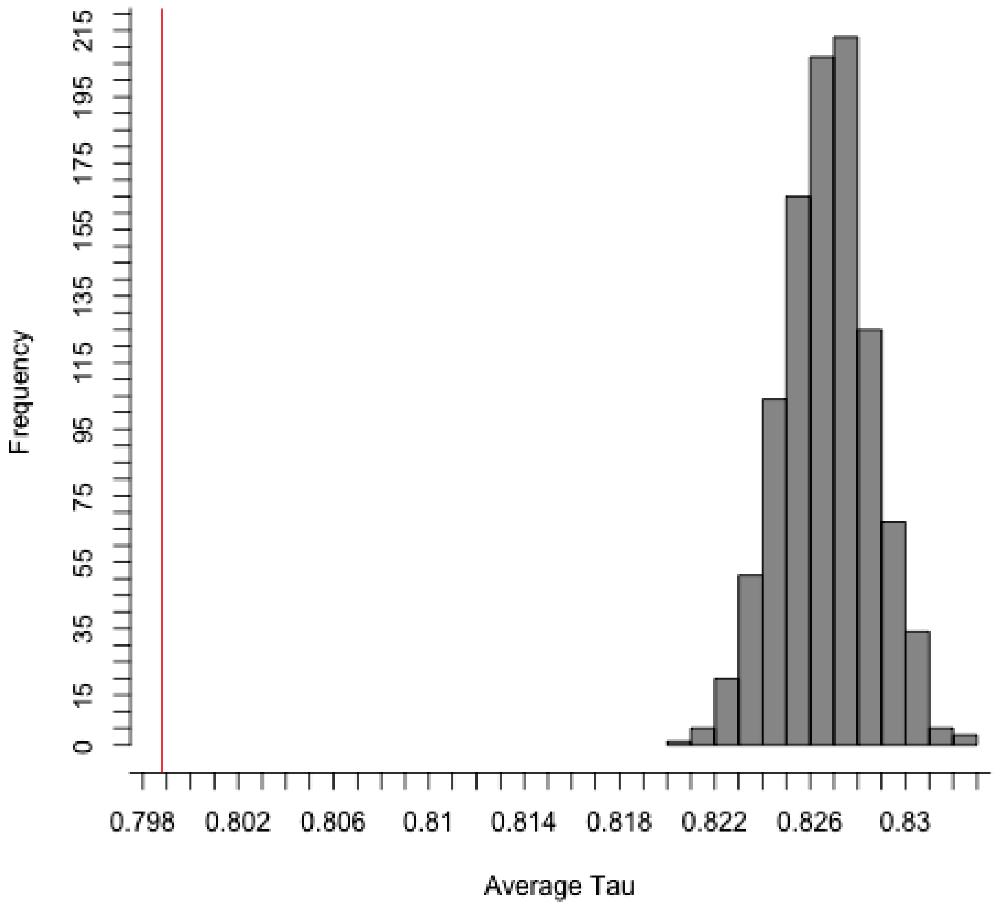
Histogram of average kendall's τ between predictor ranks for OLS and alternative rank vectors for the regression taken from Dabos & Rousseau (2004). In the alternative models the R^2 from the OLS model is reduced by a constant of 0.01. N=1000 average kendall's τ, where each average is computed from 5000 alternative weight vectors generated with the fungible weights procedure. The red line represents the median (0.905) of the average kendall's τ for the 1000 average kendall's τ's computed using predictor matrices generated by Fungible R and put through the same fungible weights procedure as the original regression. Mean=0.957, median = 0.957, s.d.=0.002, 1st quartile=0.956, 3rd quartile=0.959.

Figure 31: Fungible R Distribution of Average τ for Dabos & Rousseau (2004)



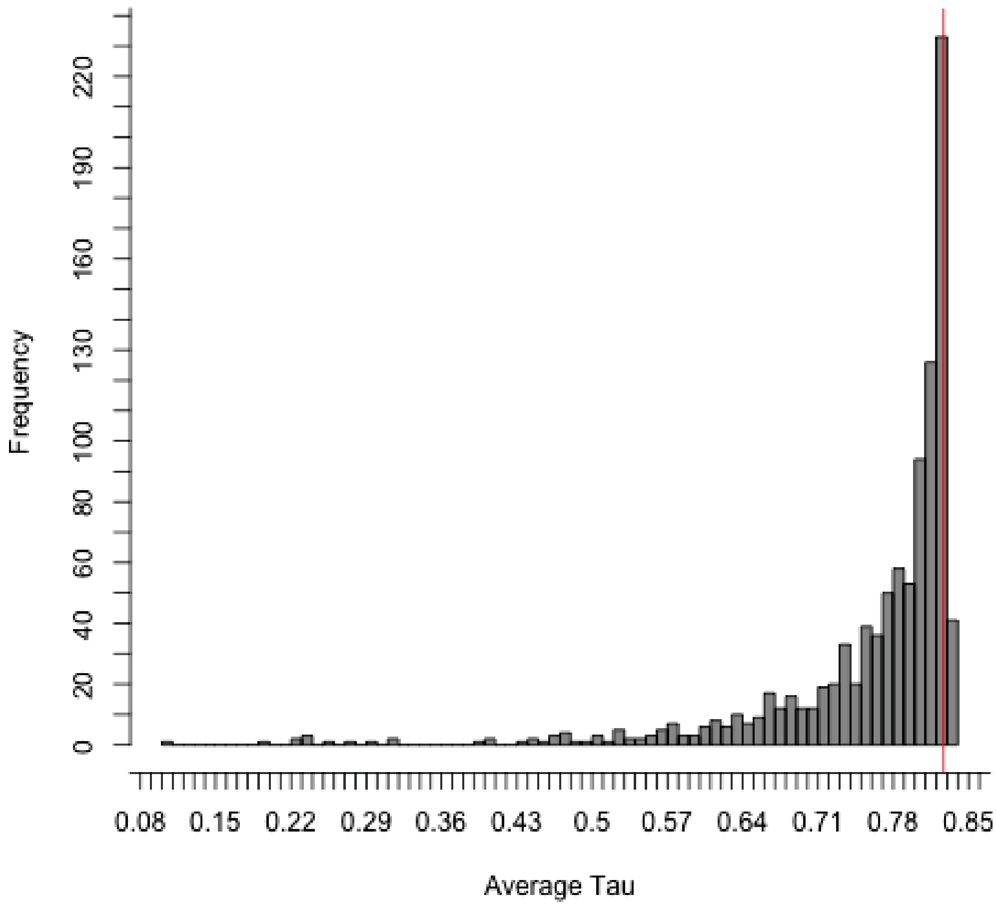
Histogram of average kendall's τ between predictor ranks for OLS and alternative rank vectors for regressions computed using predictor matrices generated by Fungible R using the original correlation and regression information from Dabos & Rousseau (2004). In the alternative models the R^2 from the OLS model is reduced by a constant of 0.01. N=1000 average kendall's τ, where each average is computed from 5000 alternative weight vectors generated with the fungible weights procedure. The red line represents the median (0.957) of the average kendall's τ for the 1000 average kendall's τ's computed using the original predictor correlation matrices and put through the same fungible weights procedure described above. Mean=0.881, median = 0.905, s.d.=0.135, 1st quartile=0.823, 3rd quartile=0.959.

Figure 32: Fungible Weights Distribution of Average τ for Klehe & Anderson (2007)



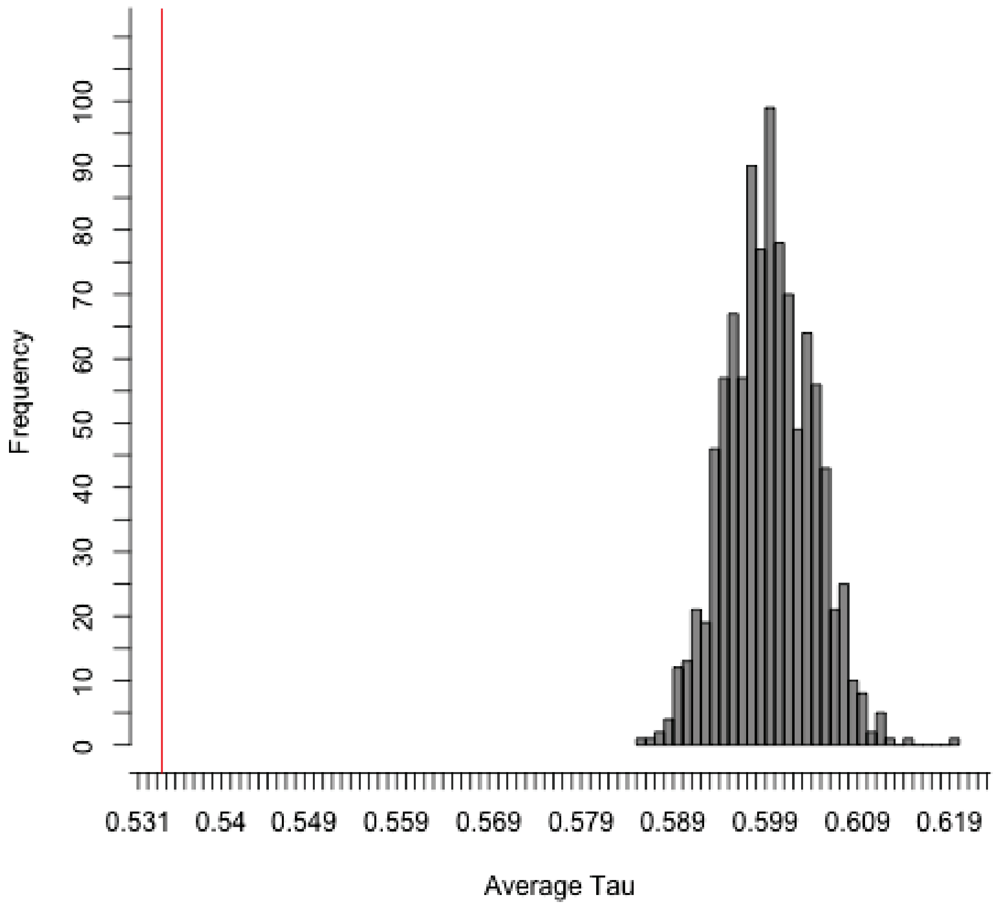
Histogram of average kendall's τ between predictor ranks for OLS and alternative rank vectors for the regression taken from Klehe & Anderson (2007). In the alternative models the R^2 from the OLS model is reduced by a constant of 0.01. N=1000 average kendall's τ, where each average is computed from 5000 alternative weight vectors generated with the fungible weights procedure. The red line represents the median (0.800) of the average kendall's τ for the 1000 average kendall's τ's computed using predictor matrices generated by Fungible R and put through the same fungible weights procedure as the original regression. Mean=0.827, median = 0.827, s.d.=0.002, 1st quartile=0.826, 3rd quartile=0.828.

Figure 33: Fungible R Distribution of Average τ for Klehe & Anderson (2007)



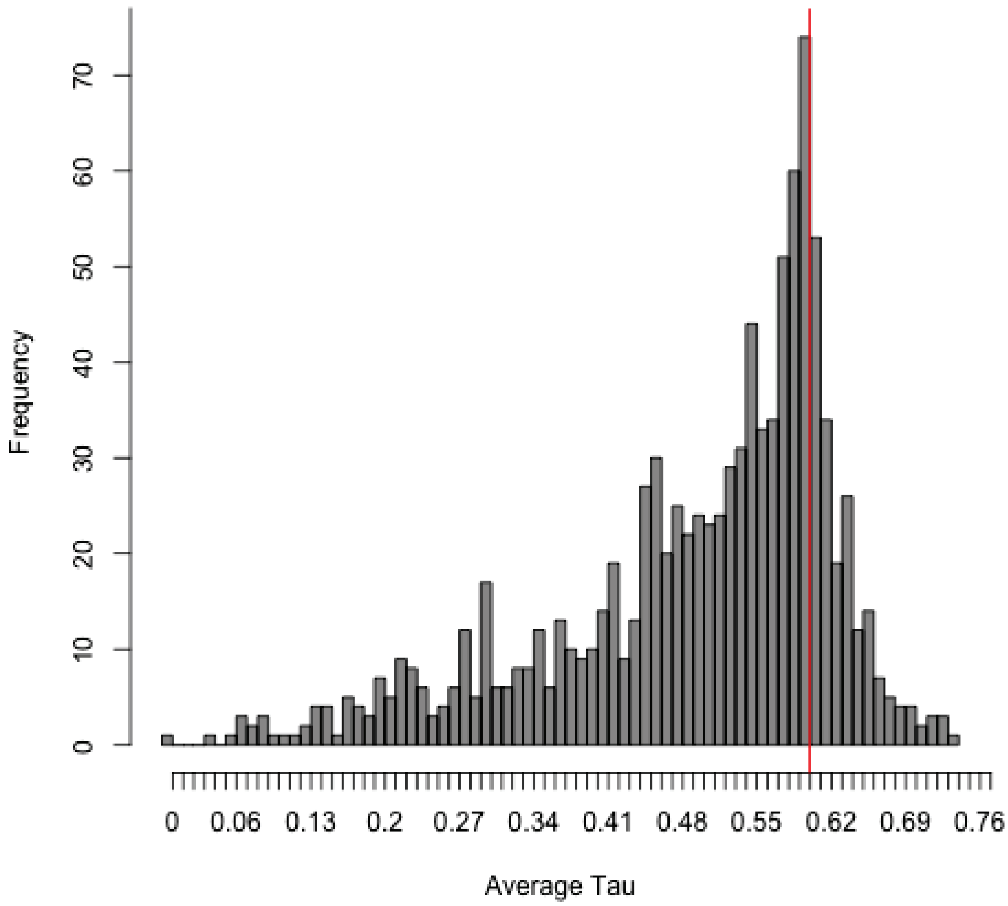
Histogram of average kendall's τ between predictor ranks for OLS and alternative rank vectors for regressions computed using predictor matrices generated by Fungible R using the original correlation and regression information from Klehe & Anderson (2007). In the alternative models the R^2 from the OLS model is reduced by a constant of 0.01. N=1000 average kendall's τ, where each average is computed from 5000 alternative weight vectors generated with the fungible weights procedure. The red line represents the median (0.827) of the average kendall's τ for the 1000 average kendall's τ's computed using the original predictor correlation matrices and put through the same fungible weights procedure described above. Mean=0.762, median = 0.800, s.d.=0.097, 1st quartile=0.740, 3rd quartile=0.821.

Figure 34: Fungible Weights Distribution of Average τ for Jiang et al. (2012)



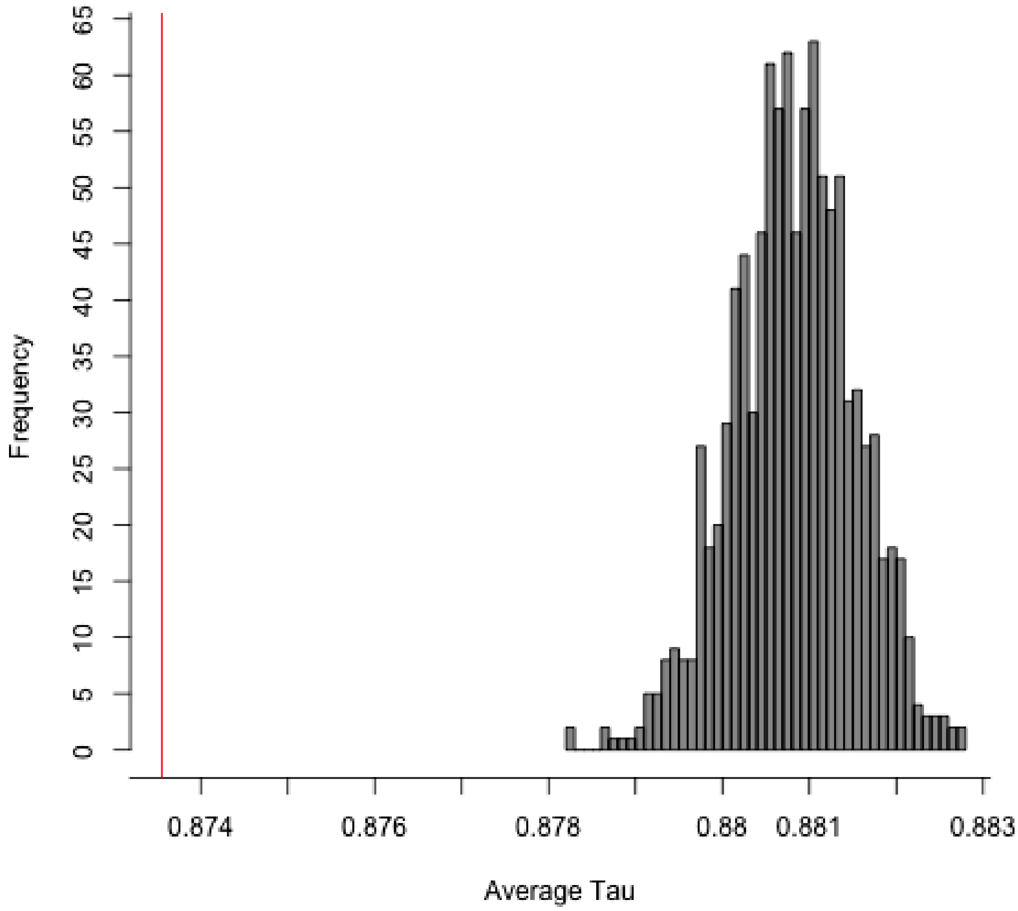
Histogram of average kendall's τ between predictor ranks for OLS and alternative rank vectors for the regression taken from Jiang et al. (2012). In the alternative models the R^2 from the OLS model is reduced by a constant of 0.01. N=1000 average kendall's τ, where each average is computed from 5000 alternative weight vectors generated with the fungible weights procedure. The red line represents the median (0.534) of the average kendall's τ for the 1000 average kendall's τ's computed using predictor matrices generated by Fungible R and put through the same fungible weights procedure as the original regression. Mean=0.599, median = 0.599, s.d.=0.005, 1st quartile=0.596, 3rd quartile=0.603.

Figure 35: Fungible R Distribution of Average τ for Jiang et al. (2012)



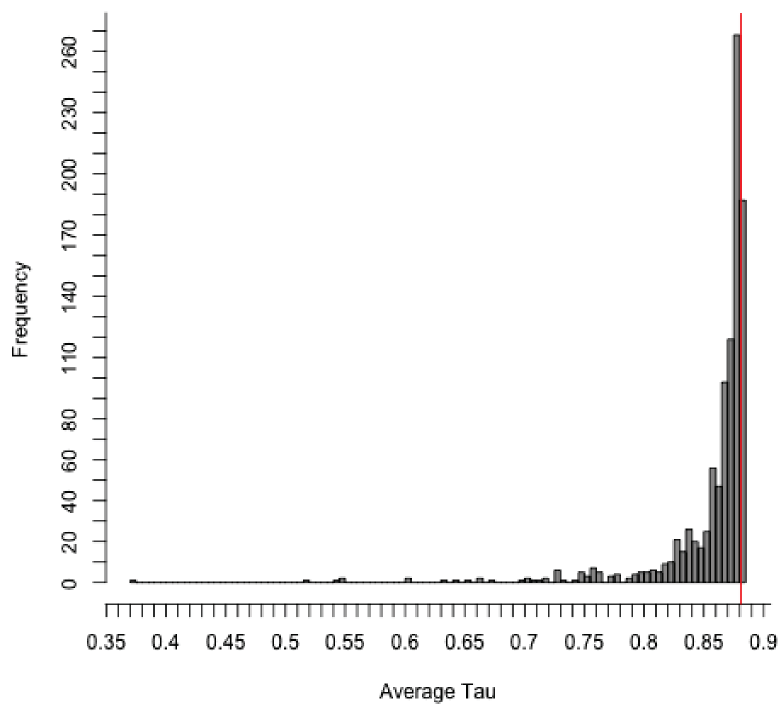
Histogram of average kendall's τ between predictor ranks for OLS and alternative rank vectors for regressions computed using predictor matrices generated by Fungible R using the original correlation and regression information from Jiang et al. (2012). In the alternative models the R^2 from the OLS model is reduced by a constant of 0.01. N=1000 average kendall's τ, where each average is computed from 5000 alternative weight vectors generated with the fungible weights procedure. The red line represents the median (0.599) of the average kendall's τ for the 1000 average kendall's τ's computed using the original predictor correlation matrices and put through the same fungible weights procedure described above. Mean=0.493, median = 0.533, s.d.=0.135, 1st quartile=0.432, 3rd quartile=0.591.

Figure 36: Fungible Weights Distribution of Average τ for Richards & Schat (2011)



Histogram of average kendall's τ between predictor ranks for OLS and alternative rank vectors for the regression taken from Richards & Schat (2011). In the alternative models the R^2 from the OLS model is reduced by a constant of 0.01. N=1000 average kendall's τ, where each average is computed from 5000 alternative weight vectors generated with the fungible weights procedure. The red line represents the median (0.873) of the average kendall's τ for the 1000 average kendall's τ's computed using predictor matrices generated by Fungible R and put through the same fungible weights procedure as the original regression. Mean=0.881, median = 0.881, s.d.=0.001, 1st quartile=0.880, 3rd quartile=0.881.

Figure 37: Fungible R Distribution of Average τ for Richards & Schat (2011)



Histogram of average kendall's τ between predictor ranks for OLS and alternative rank vectors for regressions computed using predictor matrices generated by Fungible R using the original correlation and regression information from Richards & Schat (2011). In the alternative models the R^2 from the OLS model is reduced by a constant of 0.01. N=1000 average kendall's τ, where each average is computed from 5000 alternative weight vectors generated with the fungible weights procedure. The red line represents the median (0.881) of the average kendall's τ for the 1000 average kendall's τ's computed using the original predictor correlation matrices and put through the same fungible weights procedure described above. Mean=0.858, median = 0.873, s.d.=0.044, 1st quartile=0.857, 3rd quartile=0.880.

Table 1: Summary of Relative Importance Analyses

Approach	Description	Strengths	Weaknesses
Zero-Order Correlations	Bivariate correlations between each predictor variable and the outcome variable.	Less sensitive to sampling error than beta weights. Can be used to quantify the shared variance between the predictor and outcome variable. Not affected by other predictor variables in the model. Easy to calculate.	Difficult to interpret when there is multicollinearity.
Beta Weights	The expected difference in the z-score of the outcome variable, given an increase of one standard deviation unit in the predictor while holding the value of other predictors constant.	Easy to calculate. Serve as a good starting point for further exploration.	Hard to interpret when there is multicollinearity. Capitalize on sample-specific characteristics.
Pratt Measure	The product of a predictor's zero-order correlation and its beta weights.	The sum across all predictors is equal to the model R^2 even when there is multicollinearity. Easy to calculate.	Can result in negative values that are difficult to interpret.
Structure Coefficients	Correlation between the predictor variable and the model-predicted values of the outcome variable.	Squared structure coefficients can be interpreted as the shared variance between the predicted outcome variable score and the predictor variable.	Do not identify which predictors share variance related to the outcome variable.

Commonality Coefficients	Unique effects: Measures the contribution of an individual predictor that is not shared with any other predictors. It is the squared semipartial correlation. Common effects: Quantifies each predictors contribution to predicting the outcome variable that the predictor shares with other predictor variables	Sum to the multiple R^2	The number of commonality coefficients increases exponentially with the increase in number of predictors.
Dominance Analysis	Determines importance based on comparing all pairs of predictors.	Measure of direct, total, and partial effects. Rank order is consistent across multiple fit indices.	Complex computations, with the required number of models to run increasing exponentially with the number of predictors.
Relative Weights	With uncorrelated predictors, the relative weight for each predictor is the product of the zero-order correlation and the inverse of the model R^2. When predictor variables are correlated, they are transformed into uncorrelated principal components in order to partition the variance through two regressions.	Weights usually sum to R^2. Calculations take steps to minimize the effects of multicollinearity.	The sum of the weights can exceed R^2 in the presence of suppression effects. Dependent on other predictors in the model.

Note: Information compiled from Johnson, 2000; Tonidandel & LeBreton, 2011; Nathans et al., 2012; Nimon & Oswald, 2013.

Table 2: Summary of Data Collected

Variable	Description
Journal	Journal in which article is published
Year	Year of publication
Cited by	Number of times article has been cited in Google Scholar
Regression Topic	Topic of regression analysis based on topic areas identified by Cascio and Aguinis (2008)
Author Country Affiliation	The country that the article's authors' affiliations are located in.
Number of Predictors	Number of predictors in the regression model.
Hierarchical	Whether or not the regression is part of a hierarchical regression analysis.
Correlation Present	Whether or not there is a full predictor and outcome variable correlation matrix presented in the article.
Meta Analysis	Whether or not the regression uses meta-analytic data and if it uses full meta-analytic data or partial meta-analytic data. If partial is used the number of separate metrics will be recorded.
Sample Size	The sample size used in the regression.
Conclusion: Interpreted Coefficient Sign	If the authors discussed the sign of one or more of the regression coefficients.
Conclusion: Interpreted Coefficient Size	If the authors discussed the size of one or more of the regression coefficients.
Conclusion: Interpreted Coefficient Significance	If the authors discussed the statistical significance of one or more of the regression coefficients.
Conclusion: Interpreted R^2	If the authors discussed the value of the model R^2.
Relative Importance	Whether or not a method of relative importance analysis was used and, if so, which one.
Adjusted R^2	Code if a shrinkage correction is applied, if so, which one.
κ	Condition number for all positive definite $\boldsymbol{R_X}$

Table 3: Database of Past Literature Summary Frequencies

Article Characteristic	Count	Percent
JAP	123	62.44%
AMJ	45	22.84%
Psychological Science	29	14.72%
2003	6	3.05%
2004	19	9.64%
2005	7	3.55%
2006	20	10.15%
2007	21	10.66%
2008	20	10.15%
2009	20	10.15%
2010	14	7.11%
2011	17	8.63%
2012	22	11.17%
2013	9	4.57%
2014	22	11.17%
Hierarchical	99	50.25%
Meta Analysis	20	10.15%
Correlation Present	117	59.39%
Interpreted Coefficient Sign	126	63.96%
Interpreted Coefficient Size	15	7.61%
Interpreted Coefficient Significance	173	87.82%
Interpreted R^2	76	38.58%
Relative Importance	9	4.57%
Adjusted R^2	60	30.46%

Table 4: Author Country Affiliation

Country	Number of Articles with Authors Affiliated with Country	Percent of Total Articles
Australia	8	4.06%
Belgium	4	2.03%
Canada	8	4.06%
France	4	2.03%
Germany	3	1.52%
Hong Kong	13	6.60%
India	1	0.51%
Israel	2	1.02%
Italy	1	0.51%
Japan	1	0.51%
Netherlands	13	6.60%
Phillipines	1	0.51%
Portugal	1	0.51%
Singapore	4	2.03%
South Korea	4	2.03%
Spain	1	0.51%
Sweden	1	0.51%
Switzerland	2	1.02%
Taiwan	1	0.51%
UK	13	6.60%
US	166	84.26%

Table 5: Number of Articles by Topic Area: All Journals

Topic	Article Count	Percent of Total Articles
Predictors of performance	50	25.38%
Work motivation and attitudes	40	20.30%
Work groups-teams	30	15.23%
Leader influences	21	10.66%
Societal issues	13	6.60%
Training and development	5	2.54%
Consumer behavior	5	2.54%
Decision making	4	2.03%
Performance measurement	4	2.03%
Career issues	3	1.52%
Developmental psychology	3	1.52%
Human factors	3	1.52%
Neuropsychology	3	1.52%
Reward systems	3	1.52%
Adult psychology	3	1.52%
Health psychology	2	1.02%
Research methodology	2	1.02%
Clinical interventions	1	0.51%
Psychopathology	1	0.51%
Other	1	0.51%

Table 6: Number of Articles by Topic Area: JAP and AMJ Only

Topic	Article Count	Percent of Total Articles
Predictors of performance	42	25.00%
Work motivation and attitudes	39	23.21%
Work groups-teams	29	17.26%
Leader influences	21	12.50%
Societal issues	7	4.17%
Training and development	5	2.98%
Consumer behavior	5	2.98%
Performance measurement	4	2.38%
Career issues	3	1.79%
Decision making	3	1.79%
Human factors	3	1.79%
Reward systems	3	1.52%
Research methodology	2	1.19%
Neuropsychology	1	0.60%
Other	1	0.60%

Table 7: Average τ Correlations Between Selected Relative Importance Metrics

	β_p	$r_{\boldsymbol{y}\boldsymbol{x}_p}$	GD	$\boldsymbol{\varepsilon_p}$	$r^2_{S_p}$	U	C	m_p
β_p	1.00							
$r_{\boldsymbol{y}\boldsymbol{x}_p}$	0.58	1.00						
	0.31							
GD	0.72	0.82	1.00					
	0.24	0.20						
$\boldsymbol{\varepsilon_p}$	0.72	0.81	0.97	1.00				
	0.25	0.20	0.07					
$r^2_{S_p}$	0.58	1.00	0.82	0.81	1.00			
	0.31	0.00	0.20	0.20				
U	0.90	0.58	0.75	0.74	0.58	1.00		
	0.17	0.30	0.23	0.23	0.30			
C	0.41	0.60	0.60	0.59	0.61	0.42	1.00	
	0.36	0.34	0.33	0.34	0.34	0.36		
m_p	0.78	0.78	0.86	0.86	0.78	0.78	0.51	1.00
	0.82	0.22	0.17	0.17	0.22	0.21	0.34	

Note: Average correlations are presented with standard deviations below. β_p are the OLS regression weights; $r_{\boldsymbol{y}\boldsymbol{x}_p}$ are the bivariate correlations between the predictors and the criterion; GD are the general dominance weights; $\boldsymbol{\varepsilon_p}$ are the relative weights, $r^2_{S_p}$ are the squared structure coefficients; U are the unique effects from commonality analysis; C are the common effects from commonality analysis; m_p is the Pratt measure.

Table 8: Mumford et al. (2008) Relative Importance Indices for Predictor Variables Regressed onto Task Role Performance

	β_p	$r_{\boldsymbol{yx}_p}$	GD	$\boldsymbol{\varepsilon_p}$	$r^2_{S_p}$	U	C	m_p
Overall TRT Scores	0.35	0.39	0.13	0.13	0.61	0.10	0.05	0.14
	1	1	1	1	1	1	1	1
Emotional Stability	-0.23	-0.21	0.05	0.05	0.18	0.05	0.00	0.05
	2	2	2	2	2	2	5	2
Extraversion	0.21	0.16	0.03	0.03	0.10	0.03	-0.01	0.03
	3	3	3	3	3	4	6	3
Openness	-0.21	-0.07	0.02	0.02	0.02	0.04	-0.03	0.01
	4	7	4	4	7	3	7	4
Mental Ability	0.05	0.08	0.01	0.01	0.03	0.00	0.00	0.00
	5	5	6	6	5	6	4	6
Conscientiousness	0.07	0.11	0.01	0.01	0.05	0.00	0.01	0.01
	6	4	5	5	4	5	2	5
Agreeableness	0.02	0.08	0.00	0.00	0.03	0.00	0.01	0.00
	7	6	7	7	6	7	3	7

Note: Raw values of select relative importance metrics calculated from the published predictor and criterion correlation matrices for each predictor are presented along with the associated rank orders. β_p are the OLS regression weights; $r_{\boldsymbol{yx}_p}$ are the bivariate correlations between the predictors and the criterion; GD are the general dominance weights; $\boldsymbol{\varepsilon_p}$ are the relative weights, $r^2_{S_p}$ are the squared structure coefficients; U are the unique effects from commonality analysis; C are the common effects from commonality analysis; m_p is the Pratt measure.

Table 9: Klehe & Anderson (2007) Relative Importance Indices for Predictor Variables Regressed onto Typical Performance Time 2

	β_p	$r_{\boldsymbol{yx}_p}$	GD	$\boldsymbol{\varepsilon_p}$	$r^2_{S_p}$	U	C	m_p
Direction	0.40	0.55	0.20	0.20	0.61	0.12	0.18	0.22
	1	1	1	1	1	1	1	1
Persistence	0.18	0.11	0.02	0.02	0.02	0.03	-0.02	0.02
	4	5	5	5	5	4	5	5
Computer Self Efficacy	0.26	0.44	0.11	0.11	0.39	0.04	0.14	0.11
	3	2	3	3	2	3	3	3
Task Valence	0.07	0.39	0.06	0.06	0.31	0.00	0.15	0.03
	5	4	4	4	4	5	2	2
Working Smart (Procedural Skills)	0.29	0.40	0.11	0.12	0.32	0.08	0.08	0.12
	2	3	2	2	3	2	4	4

Note: Raw values of select relative importance metrics calculated from the published predictor and criterion correlation matrices for each predictor are presented along with the associated rank orders. β_p are the OLS regression weights; $r_{\boldsymbol{yx}_p}$ are the bivariate correlations between the predictors and the criterion; GD are the general dominance weights; $\boldsymbol{\varepsilon_p}$ are the relative weights, $r^2_{S_p}$ are the squared structure coefficients; U are the unique effects from commonality analysis; C are the common effects from commonality analysis; m_p is the Pratt measure.

Table 10: Dabos & Rousseau (2004) Relative Importance Indices for Predictor Variables Regressed onto Scientist's Perception of Director Transactional Obligations

	β_p	$r_{\boldsymbol{yx}_p}$	GD	$\boldsymbol{\varepsilon_p}$	$r^2_{S_p}$	U	C	m_p
Director Transactional (D)	0.28	0.44	0.11	0.11	0.84	0.05	0.15	0.13
	1	1	1	1	1	1	1	1
Director Relational (D)	-0.22	-0.41	0.09	0.09	0.73	0.03	0.14	0.09
	2	2	2	2	2	2	2	2
Director Balanced (D)	-0.05	-0.26	0.03	0.03	0.29	0.00	0.07	0.01
	3	3	3	3	3	3	3	3

Note: Raw values of select relative importance metrics calculated from the published predictor and criterion correlation matrices for each predictor are presented along with the associated rank orders. β_p are the OLS regression weights; $r_{\boldsymbol{yx}_p}$ are the bivariate correlations between the predictors and the criterion; GD are the general dominance weights; $\boldsymbol{\varepsilon_p}$ are the relative weights, $r^2_{S_p}$ are the squared structure coefficients; U are the unique effects from commonality analysis; C are the common effects from commonality analysis; m_p is the Pratt measure.

Table 11: Gupta et al. (2013) Relative Importance Indices for Predictor Variables Regressed onto Sales Performance

	β_p	$r_{\boldsymbol{yx}_p}$	GD	$\boldsymbol{\varepsilon_p}$	$r^2_{S_p}$	U	C	m_p
Conscientiousness	0.12	0.09	0.01	0.01	0.06	0.01	-0.00	0.01
	3	3	3	3	3	3	5	3
Extraversion	-0.08	-0.06	0.01	0.01	0.03	0.00	-0.00	0.00
	4	4	4	4	4	5	6	4
Agreeableness	-0.00	-0.04	0.00	0.00	0.01	0.00	0.00	0.00
	6	6	6	6	6	6	4	6
Openness to Experience	-0.22	-0.19	0.04	0.04	0.29	0.03	0.00	0.04
	2	2	2	2	2	2	2	2
Emotional Stability	-0.07	-0.05	0.00	0.00	0.02	0.00	-0.00	0.00
	5	5	5	5	5	4	3	5
Total Sales Self Efficacy	0.29	0.23	0.06	0.06	0.42	0.06	-0.01	0.07
	1	1	1	1	1	1	1	1

Note: Raw values of select relative importance metrics calculated from the published predictor and criterion correlation matrices for each predictor are presented along with the associated rank orders. β_p are the OLS regression weights; $r_{\boldsymbol{yx}_p}$ are the bivariate correlations between the predictors and the criterion; GD are the general dominance weights; $\boldsymbol{\varepsilon_p}$ are the relative weights, $r^2_{S_p}$ are the squared structure coefficients; U are the unique effects from commonality analysis; C are the common effects from commonality analysis; m_p is the Pratt measure.

Table 12: Simulation Studies Summary of Results

Article	R^2_{OLS}	R^2_{alt}	Number of Predictors	τ mean	τ median	τ s.d.	τ min	τ max	τ Q1	τ Q3
Mumford et al.	0.248	0.238	7	0.868	0.868	0.001	0.863	0.873	0.867	0.869
(2008)	0.248	0.238	7	0.847	0.862	0.050	0.324	0.873	0.850	0.867
Dabos &	0.230	0.220	3	0.957	0.957	0.002	0.950	0.963	0.956	0.959
Rousseau (2004)	0.230	0.220	3	0.881	0.905	0.135	0.099	1.000	0.823	1.000
Klehe &	0.497	0.487	5	0.827	0.827	0.002	0.821	0.832	0.826	0.828
Anderson (2007)	0.497	0.487	5	0.762	0.799	0.097	0.110	0.836	0.740	0.821
Jiang et al.	0.224	0.214	3	0.599	0.599	0.005	0.586	0.620	0.596	0.603
(2012)	0.224	0.214	3	0.493	0.534	0.135	-0.003	0.731	0.431	0.591
Richards &	0.549	0.539	12	0.881	0.881	0.001	0.878	0.883	0.880	0.881
Schat (2011)	0.549	0.539	12	0.858	0.874	0.045	0.371	0.884	0.857	0.880

Note: Summary metrics from the simulation studies are provided above. Metrics regarding average kendall's τ between predictor ranks for OLS and alternative rank vectors are provided. For each article the top row is for the fungible weights analysis being run 1000 times on the original correlation matrices. The bottom row is for regressions computed using predictor matrices generated by using Fungible R with the original correlation and regression information to produce 1000 new predictor correlation matrices which were then put through the fungible weights analysis. Q1 and Q3 refer to the 1st and 3rd quartile, respectively.

Table 13: Summary of Relevant Results for Relative Importance and Sensitivity Analyses

Metric	N	Mean	Median	sd	Min	Max	Q1	Q3
Number of predictors	409	6.970	6.000	3.920	3.000	25.000	4.000	9.000
Sample Size	409	385.900	147.000	822.791	27.000	8839.000	85.500	288.500
κ	402	2.744	2.408	1.273	1.110	11.290	1.874	3.345
OLS R^2	402	0.284	0.258	0.196	0.000	0.835	0.127	0.414
Wherry (1931) R^2_{adj}	402	0.246	0.214	0.197	-0.110	0.082	0.082	0.368
OLS R^2-R^2_{adj}	402	0.039	0.027	0.036	0.001	0.197	0.013	0.050
% Reduction between OLS R^2 and R^2_{adj}	402	0.364	0.146	1.077	0.003	14.240	0.060	0.344
ICC across 8 relative importance metrics	402	0.810	0.830	0.130	0.035	1.000	0.730	0.910
Number of relative importance metrics (out of 8) that agree on the most important predictor	402	5.940	6.000	1.690	1.000	8.000	5.000	8.000
$\frac{\varepsilon_i}{R^2} - \frac{GD_i}{R^2}$	2803	-0.000	0.000	0.007	-0.083	0.091	0.000	0.002
$\frac{\varepsilon_i}{R^2} - \frac{m_i}{R^2}$	2803	-0.000	0.002	0.069	-0.850	0.724	-0.009	0.016
$\frac{m_i}{R^2} - \frac{GD_i}{R^2}$	2803	0.000	0.000	0.070	-0.738	0.819	-0.015	0.011
Number of alternative weight vectors with entire rank order preserved (0.01 reduction in R^2)	387	1331.000	886.500	1361.672	0.000	5000.000	149.800	2060.000

Metric	N	Mean	Median	sd	Min	Max	Q1	Q3
Number of alternative weight vectors with entire rank order preserved using absolute values of weights (0.01 reduction in R^2)	387	739.566	294.000	1010.500	0.000	5000.000	17.500	1102.000
Number of alternative weight vectors with entire rank order preserved (1% reduction in R^2)	402	2401.000	2409.000	1727.719	0.000	5000.000	843.500	3873.000
Number of alternative weight vectors that agree on top ranked predictor (0.01 reduction in R^2)	387	3835.000	3986.000	1048.311	1222.000	5000.000	2878.000	4991.000
Number of alternative weight vectors that agree on top ranked predictor using absolute values of weights(0.01 reduction in R^2)	387	2379.509	2254.000	1097.829	499.000	5000.000	1564.500	2930.500
Number of alternative weight vectors that agree on top ranked predictor (1% reduction in R^2)	402	4424.000	5000.000	839.824	1846.000	5000.000	3894.000	5000.000

Metric	N	Mean	Median	sd	Min	Max	Q1	Q3
Number of alternative weight vectors that agree on lowest ranked predictor (0.01 reduction in R^2)	387	4148.687	4712.000	988.768	1699.000	5000.000	3241.500	5000.000
Number of alternative weight vectors that agree on lowest ranked predictor using absolute values of weights(0.01 reduction in R^2)	387	3919.801	4164.000	1104.324	995.000	5000.000	995.000	5000.000
Number of alternative weight vectors that agree on lowest ranked predictor (1% reduction in R^2)	402	4646.799	5000.000	705.329	1897.000	5000.000	4796.750	5000.000
Average τ between OLS ranks and alternative ranks (0.01 reduction in R^2)	387	0.792	0.823	0.144	0.042	1.000	0.731	0.879
Average τ between OLS ranks and alternative ranks using absolute values of weights (0.01 reduction in R^2)	387	0.657	0.683	0.168	0.002	1.000	0.581	0.768

Metric	N	Mean	Median	sd	Min	Max	Q1	Q3
Average τ between OLS ranks and alternative ranks (1% reduction in R^2)	402	0.904	0.922	0.096	0.102	1.000	0.878	0.961
Minimum τ between OLS ranks and alternative ranks (0.01 reduction in R^2)	387	0.406	0.448	0.349	-1.000	1.000	0.333	0.619
Minimum τ between OLS ranks and alternative ranks using absolute values of weights (0.01 reduction in R^2)	387	0.136	0.214	0.413	-1.000	1.000	0.000	0.3970
Minimum τ between OLS ranks and alternative ranks (1% reduction in R^2)	402	0.679	0.714	0.251	-1.000	1.000	0.600	0.810
Maximum τ between OLS ranks and alternative ranks (0.01 reduction in R^2)	387	0.996	1.000	0.019	0.821	1.000	1.000	1.000
Maximum τ between OLS ranks and alternative ranks using absolute values of weights (0.01 reduction in R^2)	387	0.999	1.000	0.033	0.744	1.000	1.000	1.000

Metric	N	Mean	Median	sd	Min	Max	Q1	Q3
Maximum τ between OLS ranks and alternative ranks (1% reduction in R^2)	402	0.999	1.000	0.004	0.940	1.000	1.000	1.000
Median τ between OLS ranks and alternative ranks (0.01 reduction in R^2)	387	0.808	0.833	0.161	0.333	1.000	0.733	0.905
Median τ between OLS ranks and alternative ranks using absolute values of weights (0.01 reduction in R^2)	387	0.662	0.667	0.189	0.000	1.000	0.600	0.786
Median τ between OLS ranks and alternative ranks (1% reduction in R^2)	402	0.932	0.964	0.095	0.333	1.000	0.881	1.000
Q1 τ between OLS ranks and alternative ranks (0.01 reduction in R^2)	387	0.697	0.733	0.225	-0.333	1.000	0.643	0.820
Q1 τ between OLS ranks and alternative ranks using absolute values of weights (0.01 reduction in R^2)	387	0.530	0.600	0.247	-0.400	1.000	0.333	0.696

Metric	N	Mean	Median	sd	Min	Max	Q1	Q3
Q1 τ between OLS ranks and alternative ranks (1% reduction in R^2)	402	0.842	0.867	0.180	-0.333	1.000	0.800	1.000
Q3 τ between OLS ranks and alternative ranks (0.01 reduction in R^2)	387	0.901	0.924	0.123	0.333	1.000	0.863	1.000
Q3 τ between OLS ranks and alternative ranks using absolute values of weights (0.01 reduction in R^2)	387	0.797	0.800	0.161	0.333	1.000	0.714	0.908
Q3 τ between OLS ranks and alternative ranks (1% reduction in R^2)	402	0.967	1.000	0.070	0.333	1.000	0.944	1.000
$cos\measuredangle \boldsymbol{k_i} O \boldsymbol{k_j}$ (0.01 reduction in R^2)	387	0.927	0.963	0.107	0.199	0.995	0.923	0.976
$cos\measuredangle \boldsymbol{k_i} O \boldsymbol{k_j}$ (1% reduction in R^2)	402	0.990	0.990	0.990	0.990	0.990	0.990	0.990
Percent reduction in R^2 when reducing OLS R^2 by 0.01	387	0.931	0.964	0.089	0.167	0.995	0.924	0.976
Absolute reduction in R^2 when reducing OLS R^2 by 1%	402	0.003	0.003	0.002	0.000	0.019	0.001	0.004
$\frac{median\ a_i}{\beta_i}$ (0.01 reduction in R^2)	2738	0.442	0.1929	14.001	-265.600	484.000	-0.185	0.693

Metric	N	Mean	Median	sd	Min	Max	Q1	Q3
$\frac{mean\ a_i}{\beta_i}$ (0.01 reduction in R^2)	2738	0.564	0.196	20.068	-411.800	646.300	-0.257	0.684
$\frac{SD\ a_i}{\lvert\beta_i\rvert}$ (0.01 reduction in R^2)	2738	6.826	1.504	44.913	0.114	1512.000	0.798	3.568
$\frac{maximum\ a_i}{\beta_i}$ (0.01 reduction in R^2)	2738	-0.060	1.015	104.366	-3921.000	2149.000	-2.700	2.977
$\frac{minimum\ a_i}{\beta_i}$ (0.01 reduction in R^2)	2738	0.8728	-0.297	48.842	-600.300	2007.000	-1.558	1.431
Raw difference between R^2 between OLS and unit weights	402	0.106	0.073	0.100	0.000	0.563	0.032	0.145
Percent difference between R^2 between OLS and unit weights	402	0.350	0.339	0.176	0.001	0.811	0.223	0.470

Note: Q1 and Q3 refer to the 1st and 3rd quartile, respectively.

Appendix A: List of References Included in the Database Summary

Citations marked with an * lacked a full correlation matrix and were not included in the sensitivity and relative importance analyses, citation marked with a + included regressions that lacked a positive definite correlation matrix and those regressions were not included in the sensitivity and relative importance analyses.

Agle, B. R., Nagarajan, N. J., Sonnenfeld, J. A., & Srinivasan, D. (2006). Does CEO charisma matter? An empirical analysis of the relationships among organizational performance, environmental uncertainty, and top management team perceptions of CEO charisma. *Academy of Management Journal, 49*(1), 161-174.

*Ahlqvist, S., London, B., & Rosenthal, L. (2013). Unstable identity compatibility how gender rejection sensitivity undermines the success of women in science, technology, engineering, and mathematics fields. *Psychological Science, 24(*9), 1644-1652.

*Allen, T. D., Eby, L. T., & Lentz, E. (2006). Mentorship behaviors and mentorship quality associated with formal mentoring programs: closing the gap between research and practice. *Journal of Applied Psychology, 91*(3), 567-578.

*Ambrose, M. L., & Cropanzano, R. (2003). A longitudinal analysis of organizational fairness: an examination of reactions to tenure and promotion decisions. *Journal of Applied Psychology, 88*(2), 266-275.

Anderson, C., Spataro, S. E., & Flynn, F. J. (2008). Personality and organizational culture as determinants of influence. *Journal of Applied Psychology, 93*(3), 702-710.

*Arthurs, J. D., Hoskisson, R. E., Busenitz, L. W., & Johnson, R. A. (2008). Managerial agents watching other agents: Multiple agency conflicts regarding underpricing in IPO firms. *Academy of Management Journal, 51*(2), 277-294.

Aryee, S., Walumbwa, F.O., Seidu, E.Y.M., & Otaye, L.E. (2012). Impact of high-performance work systems on individual- and branch-level performance: Test of a multilevel model of intermediate linkages. *Journal of Applied Psychology, 97*(2), 287-300.

Balkundi, P., Kilduff, M., & Harrison, D. A. (2011). Centrality and charisma: comparing how leader networks and attributions affect team performance. *Journal of Applied Psychology, 96*(6), 1209-1222.

Bansal, P., & Clelland, I. (2004). Talking trash: Legitimacy, impression management, and unsystematic risk in the context of the natural environment. *Academy of Management Journal, 47*(1), 93-103.

Barnes, C. M., Hollenbeck, J. R., Wagner, D. T., DeRue, D. S., Nahrgang, J. D., & Schwind, K. M. (2008). Harmful help: the costs of backing-up behavior in teams. *Journal of Applied Psychology, 93*(3), 529-539.

Barnett, M. L., & King, A. A. (2008). Good fences make good neighbors: A longitudinal analysis of an industry self-regulatory institution. *Academy of Management Journal, 51*(6), 1150-1170.

Barrick, M. R., Swider, B. W., & Stewart, G. L. (2010). Initial evaluations in the interview: relationships with subsequent interviewer evaluations and employment offers. *Journal of Applied Psychology, 95*(6), 1163-1172.

*Bartram, D. (2005). The Great Eight competencies: a criterion-centric approach to validation. *Journal of Applied Psychology, 90*(6), 1185-1203.

Bell, B. S., Wiechmann, D., & Ryan, A. M. (2006). Consequences of organizational justice expectations in a selection system. *Journal of Applied Psychology, 91*(2), 455-466.

Bernerth, J. B., Taylor, S. G., Walker, H. J., & Whitman, D. S. (2012). An empirical investigation of dispositional antecedents and performance-related outcomes of credit scores. *Journal of Applied Psychology, 97*(2), 469-478.

*Blader, S. L., & Tyler, T. R. (2009). Testing and extending the group engagement model: linkages between social identity, procedural justice, economic outcomes, and extrarole behavior. *Journal of Applied Psychology, 94*(2), 445-464.

Bordia, P., Restubog, S. L. D., & Tang, R. L. (2008). When employees strike back: investigating mediating mechanisms between psychological contract breach and workplace deviance. *Journal of Applied Psychology, 93*(5), 1104-1117.

*Bowling, N. A., & Beehr, T. A. (2006). Workplace harassment from the victim's perspective: a theoretical model and meta-analysis. *Journal of Applied Psychology, 91*(5), 998-1012.

*Brown, M.E. & Treviño, L.K. (2009). Leader-follower values congruence: Are socialized charismatic leaders better able to achieve it? *Journal of Applied Psychology, 94*(2), 478-490.

Brown, M.E., & Treviño, L.K. (2006). Socialized charismatic leadership, values congruence, and deviance in work groups. *Journal of Applied Psychology, 91*(4), 954-962.

Brown, R. P., Osterman, L. L., & Barnes, C. D. (2009). School violence and the culture of honor. *Psychological Science, 20*(11), 1400-1405.

*Buchan, N. R., Brewer, M. B., Grimalda, G., Wilson, R. K., Fatas, E., & Foddy, M. (2011). Global social identity and global cooperation. *Psychological science, 22*(6), 821-828.

*Cable, D. M., & Kay, V. S. (2012). Striving for self-verification during organizational entry. *Academy of Management Journal, 55*(2), 360-380.

Carton, A. M., Murphy, C., & Clark, J. R. (2014). A (blurry) vision of the future: How leader rhetoric about ultimate goals influences performance. *Academy of Management Journal, 57*(6), 1544-1570.

*Chao, M. M., Chen, J., Roisman, G. I., & Hong, Y. Y. (2007). Essentializing race: Implications for bicultural individuals' cognition and physiological reactivity. *Psychological science, 18*(4), 341-348.

Charles, S. T., Piazza, J. R., Mogle, J., Sliwinski, M. J., & Almeida, D. M. (2013). The wear and tear of daily stressors on mental health. *Psychological science, 24*(5), 733-741.

Chen, G., Sharma, P.N., Edinger, S.K., Shapiro, D.L., & Farh, J. (2011). Motivating and demotivating forces in teams: Cross-level influences of empowering leadership and relationship conflict. *Journal of Applied Psychology, 96*(3), 541-557.

Chen, G., Thomas, B., & Wallace, J.C. (2005). A multilevel examination of the relationships among training outcomes, mediating regulatory processes, and adaptive performance. *Journal of Applied Psychology, 90*(5), 827-841.

Christmann, P. (2004). Multinational companies and the natural environment: Determinants of global environmental policy. *Academy of Management Journal, 47*(5), 747-760.

+Chun, J. S., & Choi, J. N. (2014). Members' needs, intragroup conflict, and group performance. *Journal of Applied Psychology, 99*(3), 437-450.

*Collins, C. J., & Smith, K. G. (2006). Knowledge exchange and combination: The role of human resource practices in the performance of high-technology firms. *Academy of management journal, 49*(3), 544-560.

Conlon, D. E., Morgeson, F. P., McNamara, G., Wiseman, R. M., & Skilton, P. F. (2006). From the editors: examining the impact and role of special issue and regular journal articles in the field of management. *Academy of Management Journal, 49*(5), 857-872.

*Cook, R., Brewer, R., Shah, P., & Bird, G. (2013). Alexithymia, not autism, predicts poor recognition of emotional facial expressions. *Psychological Science, 24*(5), 723-732.

Courtright, S. H., Colbert, A. E., & Choi, D. (2014). Fired up or burned out? How developmental challenge differentially impacts leader behavior. *Journal of Applied Psychology, 99*(4), 681-696.

Cross, R., & Cummings, J. N. (2004). Tie and network correlates of individual performance in knowledge-intensive work. *Academy of Management Journal,* *47*(6), 928-937.

*Curhan, J. R., & Pentland, A. (2007). Thin slices of negotiation: predicting outcomes from conversational dynamics within the first 5 minutes. *Journal of Applied Psychology, 92*(3), 802-811.

Curhan, J. R., Elfenbein, H. A., & Kilduff, G. J. (2009). Getting off on the right foot: subjective value versus economic value in predicting longitudinal job outcomes from job offer negotiations. *Journal of Applied Psychology, 94*(2), 524-534.

Dabos, G. E., & Rousseau, D. M. (2004). Mutuality and reciprocity in the psychological contracts of employees and employers. *Journal of Applied Psychology, 89*(1), 52-72.

Davidson, W. N., Jiraporn, P., Kim, Y. S., & Nemec, C. (2004). Earnings management following duality-creating successions: Ethnostatistics, impression management, and agency theory. *Academy of Management Journal, 47*(2), 267-275.

*De Jong, B. A., & Elfring, T. (2010). How does trust affect the performance of ongoing teams? The mediating role of reflexivity, monitoring, and effort. *Academy of Management Journal, 53*(3), 535-549.

De Jong, J. P., Curşeu, P. L., & Leenders, R. T. A. (2014). When do bad apples not spoil the barrel? Negative relationships in teams, team performance, and buffering mechanisms. *Journal of Applied Psychology, 99*(3), 514-522.

De Vries, T. A., Walter, F., Van der Vegt, G. S., & Essens, P. J. (2014). Antecedents of individuals' interteam coordination: Broad functional experiences as a mixed blessing. *Academy of Management Journal, 57*(5), 1334-1359.

DeChurch, L. A., & Marks, M. A. (2006). Leadership in multiteam systems. *Journal of Applied Psychology, 91*(2), 311-329.

*DeChurch, L. A., & Mesmer-Magnus, J. R. (2010). The cognitive underpinnings of effective teamwork: a meta-analysis.*Journal of Applied Psychology, 95*(1), 32-53.

DeChurch, L. A., Mesmer-Magnus, J. R., & Doty, D. (2013). Moving beyond relationship and task conflict: Toward a process-state perspective. *Journal of Applied Psychology, 98*(4), 559-578.

*DeKay, M. L., & Kim, T. G. (2005). When things don't add up: The role of perceived fungibility in repeated-play decisions. *Psychological Science, 16*(9), 667-672.

DeRue, D. S., & Morgeson, F. P. (2007). Stability and change in person-team and person-role fit over time: the effects of growth satisfaction, performance, and general self-efficacy. *Journal of Applied Psychology, 92*(5), 1242-1253.

DeRue, D. S., Hollenbeck, J. R., Johnson, M. D., Ilgen, D. R., & Jundt, D. K. (2008). How different team downsizing approaches influence team-level adaptation and performance. *Academy of Management Journal, 51*(1), 182-196.

Detert, J. R., Treviño, L. K., & Sweitzer, V. L. (2008). Moral disengagement in ethical decision making: a study of antecedents and outcomes. *Journal of Applied Psychology, 93*(2), 374-391.

Detert, J. R., Trevino, L. K., Burris, E. R., & Andiappan, M. (2007). Managerial modes of influence and counterproductivity in organizations: a longitudinal business-unit-level investigation. *Journal of Applied Psychology, 92*(4), 993-1005.

Dierdorff, E. C., & Morgeson, F. P. (2007). Consensus in work role requirements: the influence of discrete occupational context on role expectations. *Journal of Applied Psychology, 92*(5), 1228-1241.

+Drescher, M. A., Korsgaard, M. A., Welpe, I. M., Picot, A., & Wigand, R. T. (2014). The dynamics of shared leadership: Building trust and enhancing performance. *Journal of Applied Psychology, 99*(5), 771-783.

*Duckworth, A. L., & Seligman, M. E. (2005). Self-discipline outdoes IQ in predicting academic performance of adolescents. *Psychological Science, 16*(12), 939-944.

*Dudley, N. M., Orvis, K. A., Lebiecki, J. E., & Cortina, J. M. (2006). A meta-analytic investigation of conscientiousness in the prediction of job performance: examining the intercorrelations and the incremental validity of narrow traits. *Journal of Applied Psychology, 91*(1), 40-57.

Dunlap, W. P., & Landis, R. S. (1998). Interpretations of multiple regression borrowed from factor analysis and canonical correlation. *The Journal of General Psychology, 125*(4), 397-407.

Duffy, M. K., Scott, K. L., Shaw, J. D., Tepper, B. J., & Aquino, K. (2012). A social context model of envy and social undermining. *Academy of Management Journal, 55*(3), 643-666.

*Durand, R., & Jourdan, J. (2012). Jules or Jim: Alternative conformity to minority logics. *Academy of Management Journal, 55*(6), 1295-1315.

Eby, L. T., Durley, J. R., Evans, S. C., & Ragins, B. R. (2008). Mentors' perceptions of negative mentoring experiences: scale development and nomological validation. *Journal of Applied Psychology, 93*(2), 358-373.

Edwards, B. D., Day, E. A., Arthur Jr, W., & Bell, S. T. (2006). Relationships among team ability composition, team mental models, and team performance. *Journal of Applied Psychology, 91*(3), 727-736.

*Ellis, S., Ganzach, Y., Castle, E., & Sekely, G. (2010). The effect of filmed versus personal after-event reviews on task performance: the mediating and moderating role of self-efficacy. *Journal of Applied Psychology, 95*(1), 122-131.

*Fahsing, I. A., Ask, K., & Granhag, P. A. (2004). The man behind the mask: accuracy and predictors of eyewitness offender descriptions. *Journal of Applied Psychology, 89*(4), 722-729.

*Fast, N. J., Heath, C., & Wu, G. (2009). Common ground and cultural prominence: How conversation reinforces culture. *Psychological Science, 20*(7), 904-911.

*Feldman, R., Weller, A., Zagoory-Sharon, O., & Levine, A. (2007). Evidence for a neuroendocrinological foundation of human affiliation: plasma oxytocin levels across pregnancy and the postpartum period predict mother-infant bonding. *Psychological Science, 18*(11), 965-970.

Firth, B. M., Chen, G., Kirkman, B. L., & Kim, K. (2014). Newcomers abroad: Expatriate adaptation during early phases of international assignments. *Academy of Management Journal, 57*(1), 280-300.

Fisher, D. M. (2014). Distinguishing between taskwork and teamwork planning in teams: Relations with coordination and interpersonal processes. *Journal of Applied Psychology, 99*(3), 423-436.

Fisher, D. M., Bell, S. T., Dierdorff, E. C., & Belohlav, J. A. (2012). Facet personality and surface-level diversity as team mental model antecedents: implications for implicit coordination. *Journal of Applied Psychology, 97*(4), 825-841.

*Flaxman, P. E., Ménard, J., Bond, F. W., & Kinman, G. (2012). Academics' experiences of a respite from work: effects of self-critical perfectionism and perseverative cognition on postrespite well-being. *Journal of Applied Psychology, 97*(4), 854-865.

Flynn, F. J., & Schaumberg, R. L. (2012). When feeling bad leads to feeling good: Guilt-proneness and affective organizational commitment. *Journal of Applied Psychology, 97*(1), 124-133.

*Ford, M. T., Heinen, B. A., & Langkamer, K. L. (2007). Work and family satisfaction and conflict: a meta-analysis of cross-domain relations. *Journal of Applied Psychology, 92*(1), 57-78.

*Förster, J., & Higgins, E. T. (2005). How global versus local perception fits regulatory focus. *Psychological Science, 16*(8), 631-636.

*Friedman, R., Liu, W., Chen, C. C., & Chi, S. C. S. (2007). Causal attribution for interfirm contract violation: a comparative study of Chinese and American commercial arbitrators. *Journal of Applied Psychology, 92*(3), 856-864.

Fritz, C., & Sonnentag, S. (2006). Recovery, well-being, and performance-related outcomes: the role of workload and vacation experiences. *Journal of Applied Psychology, 91*(4), 936-945.

Fritz, C., Yankelevich, M., Zarubin, A., & Barger, P. (2010). Happy, healthy, and productive: the role of detachment from work during nonwork time. *Journal of Applied Psychology, 95*(5), 977-983.

Gardner, H. K., Gino, F., & Staats, B. R. (2012). Dynamically integrating knowledge in teams: Transforming resources into performance. *Academy of Management Journal, 55*(4), 998-1022.

*Gibson, C. B., & Birkinshaw, J. (2004). The antecedents, consequences, and mediating role of organizational ambidexterity. *Academy of management Journal, 47*(2), 209-226.

*Gibson, C. B., Porath, C. L., Benson, G. S., & Lawler III, E. E. (2007). What results when firms implement practices: the differential relationship between specific practices, firm financial performance, customer service, and quality. *Journal of Applied Psychology, 92*(6), 1467-1480.

Glebbeek, A. C., & Bax, E. H. (2004). Is high employee turnover really harmful? An empirical test using company records. *Academy of Management Journal, 47*(2), 277-286.

Gong, Y., Law, K. S., Chang, S., & Xin, K. R. (2009). Human resources management and firm performance: The differential role of managerial affective and continuance commitment. *Journal of Applied Psychology, 94*(1), 263-275.

Gonzalez-Mulé, E., DeGeest, D. S., McCormick, B. W., Seong, J. Y., & Brown, K. G. (2014). Can we get some cooperation around here? The mediating role of group norms on the relationship between team personality and individual helping behaviors. *Journal of Applied Psychology, 99*(5), 988-999.

Gonzalez-Mulé, E., Mount, M. K., & Oh, I. S. (2014). A meta-analysis of the relationship between general mental ability and nontask performance. *Journal of Applied Psychology, 99*(6), 1222-1243.

*Grant, A. M., Berg, J. M., & Cable, D. M. (2014). Job titles as identity badges: How self-reflective titles can reduce emotional exhaustion. *Academy of Management Journal, 57*(4), 1201-1225.

*Grzywacz, J. G., Arcury, T. A., Marín, A., Carrillo, L., Burke, B., Coates, M. L., & Quandt, S. A. (2007). Work-family conflict: Experiences and health implications among immigrant Latinos. *Journal of Applied Psychology, 92*(4), 1119-1130.

Gupta, N., Ganster, D. C., & Kepes, S. (2013). Assessing the validity of sales self-efficacy: A cautionary tale. *Journal of Applied Psychology, 98*(4), 690-700.

*Hakuta, K., Bialystok, E., & Wiley, E. (2003). Critical evidence: A test of the critical-period hypothesis for second-language acquisition. *Psychological Science, 14*(1), 31-38.

Hannah, S. T., Balthazard, P. A., Waldman, D. A., Jennings, P. L., & Thatcher, R. W. (2013). The psychological and neurological bases of leader self-complexity and effects on adaptive decision-making. *Journal of Applied Psychology, 98*(3), 393.

+Harris, M. M., Anseel, F., & Lievens, F. (2008). Keeping up with the Joneses: a field study of the relationships among upward, lateral, and downward comparisons and pay level satisfaction. *Journal of Applied Psychology, 93*(3), 665-673.

*Hart, D., Atkins, R., & Youniss, J. (2005). Knowledge, youth bulges, and rebellion. *Psychological Science, 16*(8), 661-662.

*Hawkley, L. C., Browne, M. W., & Cacioppo, J. T. (2005). How can I connect with thee? Let me count the ways. *Psychological Science, 16*(10), 798-804.

Hay, D. F., Mundy, L., Roberts, S., Carta, R., Waters, C. S., Perra, Jones, R., Jones, I., Goodyer, I., Harold, G., Thapar, A. & van Goozen, S. (2011). Known risk factors for violence predict 12-month-old infants' aggressiveness with peers. *Psychological science, 22*(9), 1205-1211.

Heimeriks, K. H., Schijven, M., & Gates, S. (2012). Manifestations of higher-order routines: The underlying mechanisms of deliberate learning in the context of postacquisition integration. *Academy of Management Journal, 55*(3), 703-726.

Hewlin, P. F. (2009). Wearing the cloak: antecedents and consequences of creating facades of conformity. *Journal of Applied Psychology, 94*(3), 727-741.

Hinkin, T. R., & Schriesheim, C. A. (2008). An examination of "nonleadership": from laissez-faire leadership to leader reward omission and punishment omission. *Journal of Applied Psychology, 93*(6), 1234-1248.

Hirschfeld, R. R., Cole, M. S., Bernerth, J. B., & Rizzuto, T. E. (2013). Voluntary survey completion among team members: Implications of noncompliance and missing data for multilevel research. *Journal of Applied Psychology, 98*(3), 454-468.

Hirschfeld, R.R. & Bernerth (2008). Mental efficacy and physical efficacy at the team level: Inputs and outcomes among newly formed action teams. *Journal of Applied Psychology, 93*(6), 1429-1437.

*Hodson, G., & Costello, K. (2007). Interpersonal disgust, ideological orientations, and dehumanization as predictors of intergroup attitudes. *Psychological Science, 18*(8), 691-698.

*Houben, K., Wiers, R. W., & Jansen, A. (2011). Getting a grip on drinking behavior: training working memory to reduce alcohol abuse. *Psychological Science, 22*(7), 968-975.

+Hult, G. T. M., Ketchen, D. J., & Slater, S. F. (2004). Information processing, knowledge development, and strategic supply chain performance. *Academy of Management Journal, 47*(2), 241-253.

*Humphrey, S. E., Nahrgang, J. D., & Morgeson, F. P. (2007). Integrating motivational, social, and contextual work design features: a meta-analytic summary and theoretical extension of the work design literature. *Journal of Applied Psychology, 92*(5), 1332-1356.

Jackson, C.L., Colquitt, J.A., Wesson, M.J., & Zapata-Phelan, C.P. (2006). Psychological Collectivism: A measurement validation and linkage to group member performance. *Journal of Applied Psychology, 91*(4), 884-899.

Janssen, O., & Van Yperen, N. W. (2004). Employees' goal orientations, the quality of leader-member exchange, and the outcomes of job performance and job satisfaction. *Academy of Management Journal, 47*(3), 368-384.

Jehn, K. A., Rispens, S., & Thatcher, S. M. (2010). The effects of conflict asymmetry on work group and individual outcomes. *Academy of Management Journal, 53*(3), 596-616.

Jiang, K., Lepak, D. P., Hu, J., & Baer, J. C. (2012). How does human resource management influence organizational outcomes? A meta-analytic investigation of mediating mechanisms. *Academy of Management Journal, 55*(6), 1264-1294.

Johnson, M. D., Morgeson, F. P., Ilgen, D. R., Meyer, C. J., & Lloyd, J. W. (2006). Multiple professional identities: examining differences in identification across work-related targets. *Journal of Applied Psychology, 91*(2), 498-506.

*Johnson, R. E., & Lord, R. G. (2010). Implicit effects of justice on self-identity. *Journal of Applied Psychology, 95*(4), 681-695.

*Judge, T. A., & Cable, D. M. (2011). When it comes to pay, do the thin win? The effect of weight on pay for men and women. *Journal of Applied Psychology, 96*(1), 95-112.

*Judge, T. A., & Piccolo, R. F. (2004). Transformational and transactional leadership: a meta-analytic test of their relative validity. *Journal of Applied Psychology, 89*(5), 755-768.

Judge, T. A., Jackson, C. L., Shaw, J. C., Scott, B. A., & Rich, B. L. (2007). Self-efficacy and work-related performance: the integral role of individual differences. *Journal of Applied Psychology, 92*(1), 107-127.

Judge, T.A., LePine, J.A., & Rich, B.L. (2006). Loving yourself abundantly: Relationship of the narcissistic personality to self- and other perceptions of workplace deviance, leadership, and task and contextual performance. *Journal of Applied Psychology, 91*(4), 762-776.

*Kaplan, S., Bradley, J. C., Luchman, J. N., & Haynes, D. (2009). On the role of positive and negative affectivity in job performance: a meta-analytic investigation. *Journal of Applied Psychology, 94*(1), 162-176.

*Khaire, M., & Wadhwani, R. D. (2010). Changing landscapes: The construction of meaning and value in a new market category—Modern Indian art. *Academy of Management Journal, 53*(6), 1281-1304.

Kim, H., & Jensen, M. (2014). Audience heterogeneity and the effectiveness of market signals: How to overcome liabilities of foreignness in film exports?. *Academy of Management Journal, 57*(5), 1360-1384.

Kirkman, B. L., Rosen, B., Tesluk, P. E., & Gibson, C. B. (2004). The impact of team empowerment on virtual team performance: The moderating role of face-to-face interaction. *Academy of Management Journal, 47*(2), 175-192.

Klehe, U. C., & Anderson, N. (2007). Working hard and working smart: motivation and ability during typical and maximum performance. *Journal of Applied Psychology, 92*(4), 978-992.

*Klein, H. J., Cooper, J. T., Molloy, J. C., & Swanson, J. A. (2014). The assessment of commitment: Advantages of a unidimensional, target-free approach. *Journal of Applied Psychology, 99*(2), 222-238.

Kraimer, M. L., Shaffer, M. A., Harrison, D. A., & Ren, H. (2012). No place like home? An identity strain perspective on repatriate turnover. *Academy of Management Journal, 55*(2), 399-420.

*Kraus, M. W., & Keltner, D. (2009). Signs of socioeconomic status a thin-slicing approach. *Psychological Science, 20*(1), 99-106.

*Krause, R., Whitler, K. A., & Semadeni, M. (2014). Power to the principals! An experimental look at shareholder say-on-pay voting. *Academy of Management Journal, 57*(1), 94-115.

*Kwon, S., & Weingart, L. R. (2004). Unilateral concessions from the other party: concession behavior, attributions, and negotiation judgments. *Journal of Applied Psychology, 89*(2), 263-278.

Kwong, J. Y., & Wong, K. F. E. (2014). Reducing and exaggerating escalation of commitment by option partitioning. *Journal of Applied Psychology, 99*(4), 697-712.

Lai, L., Rousseau, D.M., & Chang, K.T.T. (2009). Idiosyncratic deals: Coworkers as interested third parties. *Journal of Applied Psychology, 94*(2), 547-556.

*Lam, C. K., Van der Vegt, G. S., Walter, F., & Huang, X. (2011). Harming high performers: a social comparison perspective on interpersonal harming in work teams. *Journal of Applied Psychology, 96*(3), 588-601.

*Lammers, J., Stoker, J. I., & Stapel, D. A. (2009). Differentiating social and personal power: Opposite effects on stereotyping, but parallel effects on behavioral approach tendencies. *Psychological Science, 20*(12), 1543-1548.

Leavitt, K., Reynolds, S. J., Barnes, C. M., Schilpzand, P., & Hannah, S. T. (2012). Different hats, different obligations: Plural occupational identities and situated moral judgments. *Academy of Management Journal, 55*(6), 1316-1333.

Lee, J. J., Gino, F., & Staats, B. R. (2014). Rainmakers: Why bad weather means good productivity. *Journal of Applied Psychology, 99*(3), 504.

Lee, T. W., Mitchell, T. R., Sablynski, C. J., Burton, J. P., & Holtom, B. C. (2004). The effects of job embeddedness on organizational citizenship, job performance, volitional absences, and voluntary turnover. *Academy of Management Journal, 47*(5), 711-722.

*Lehmann-Willenbrock, N., & Allen, J. A. (2014). How fun are your meetings? Investigating the relationship between humor patterns in team interactions and team performance. *Journal of Applied Psychology, 99*(6), 1278-1287.

*Leslie, L. M., Mayer, D. M., & Kravitz, D. A. (2014). The stigma of affirmative action: a stereotyping-based theory and meta-analytic test of the consequences for performance. *Academy of Management Journal, 57*(4), 964-989.

*Li, A. N., & Liao, H. (2014). How do leader–member exchange quality and differentiation affect performance in teams? An integrated multilevel dual process model. *Journal of Applied Psychology, 99*(5), 847-866.

Lian, H., Ferris, D. L., & Brown, D. J. (2012). Does power distance exacerbate or mitigate the effects of abusive supervision? It depends on the outcome. *Journal of Applied Psychology, 97*(1), 107-123.

Lievens, F., & Sackett, P. R. (2012). The validity of interpersonal skills assessment via situational judgment tests for predicting academic success and job performance. *Journal of Applied Psychology, 97*(2), 460-468.

*Lievens, F., Ones, D. S., & Dilchert, S. (2009). Personality scale validities increase throughout medical school. *Journal of Applied Psychology, 94*(6), 1514-1535.

Lim, B. & Ployhart, R.E. (2004). Transformational leadership: Relations to the five-factor model and team performance in typical and maximum contexts.

Journal of Applied Psychology, 89(4), 610-621.

*Liu, L. A., Chua, C. H., & Stahl, G. K. (2010). Quality of communication experience: definition, measurement, and implications for intercultural negotiations. *Journal of Applied Psychology, 95*(3), 469-487.

*Livingston, R. W., & Pearce, N. A. (2009). The teddy-bear effect does having a baby face benefit black chief executive officers?. *Psychological Science, 20*(10), 1229-1236.

Madjar, N., Greenberg, E., & Chen, Z. (2011). Factors for radical creativity, incremental creativity, and routine, noncreative performance. *Journal of Applied Psychology, 96*(4), 730-743.

*Major, D. A., Turner, J. E., & Fletcher, T. D. (2006). Linking proactive personality and the Big Five to motivation to learn and development activity. *Journal of applied psychology, 91*(4), 927-935.

McDonald, M. L., & Westphal, J. D. (2010). A little help here? Board control, CEO identification with the corporate elite, and strategic help provided to CEOs at other firms. *Academy of Management Journal, 53*(2), 343-370.

*McFerran, B., & Mukhopadhyay, A. (2013). Lay theories of obesity predict actual body mass. *Psychological Science, 24*(8), 1428-1436.

*Miller, K. D., & Chen, W. R. (2004). Variable organizational risk preferences: Tests of the March-Shapira model. *Academy of Management Journal, 47*(1), 105-115.

Moon, H., Kamdar, D., Mayer, D. M., & Takeuchi, R. (2008). Me or we? The role of personality and justice as other-centered antecedents to innovative citizenship behaviors within organizations. *Journal of Applied Psychology, 93*(1), 84-94.

Mumford, T. V., Van Iddekinge, C. H., Morgeson, F. P., & Campion, M. A. (2008). The team role test: development and validation of a team role knowledge situational judgment test. *Journal of Applied Psychology, 93*(2), 250-267.

*Nahrgang, J. D., Morgeson, F. P., & Hofmann, D. A. (2011). Safety at work: a meta-analytic investigation of the link between job demands, job resources, burnout, engagement, and safety outcomes. *Journal of Applied Psychology, 96*(1), 71-94

*Neubert, M. J., Kacmar, K. M., Carlson, D. S., Chonko, L. B., & Roberts, J. A. (2008). Regulatory focus as a mediator of the influence of initiating structure and servant leadership on employee behavior. *Journal of Applied Psychology*, 93(6), 1220-1233.

Nifadkar, S., Tsui, A. S., & Ashforth, B. E. (2012). The way you make me feel and behave: Supervisor-triggered newcomer affect and approach-avoidance behavior. *Academy of Management Journal, 55*(5), 1146-1168.

*Noguchi, K., Handley, I. M., & Albarracín, D. (2011). Participating in Politics Resembles Physical Activity General Action Patterns in International Archives, United States Archives, and Experiments. *Psychological Science, 22*(2), 235-242.

*O'Boyle Jr, E. H., Forsyth, D. R., Banks, G. C., & McDaniel, M. A. (2012). A meta-analysis of the dark triad and work behavior: A social exchange perspective. *Journal of Applied Psychology, 97*(3), 557-579.

Oh, H., & Kilduff, M. (2008). The ripple effect of personality on social structure: self-monitoring origins of network brokerage. *Journal of Applied Psychology, 93*(5), 1155-1164.

*Pase, M. P., Stough, C., Grima, N. A., Harris, E., Macpherson, H., Scholey, A. B., & Pipingas, A. (2013). Blood pressure and cognitive function the role of central aortic and brachial pressures. *Psychological Science, 24*(11), 2173-2181.

*Pearsall, M. J., Christian, M. S., & Ellis, A. P. (2010). Motivating interdependent teams: individual rewards, shared rewards, or something in between?. *Journal of Applied Psychology, 95*(1), 183-191.

Porath, C.L. & Bateman, T.S. (2006). Self-regulation: From goal orientation to job performance. *Journal of Applied Psychology, 91*(1), 185-192.

*Propper, R. E., Stickgold, R., Keeley, R., & Christman, S. D. (2007). Is television traumatic?: Dreams, stress, and media exposure in the aftermath of September 11, 2001. *Psychological Science, 18*(4), 334-340.

Ragins, B. R., Singh, R., & Cornwell, J. M. (2007). Making the invisible visible: fear and disclosure of sexual orientation at work. *Journal of Applied Psychology, 92*(4), 1103-1118.

Raja, U., Johns, G., & Ntalianis, F. (2004). The impact of personality on psychological contracts. *Academy of Management Journal, 47*(3), 350-367.

Raub, S., & Liao, H. (2012). Doing the right thing without being told: joint effects of initiative climate and general self-efficacy on employee proactive customer service performance. *Journal of Applied Psychology, 97*(3), 651-667.

Raver, J. L., & Nishii, L. H. (2010). Once, twice, or three times as harmful? Ethnic harassment, gender harassment, and generalized workplace harassment. *Journal of Applied Psychology, 95*(2), 236.

Reynolds, S. J. (2008). Moral attentiveness: Who pays attention to the moral aspects of life?. *Journal of Applied Psychology, 93*(5), 1027-1041.

Reynolds, S. J., Leavitt, K., & DeCelles, K. A. (2010). Automatic ethics: the effects of implicit assumptions and contextual cues on moral behavior. *Journal of Applied Psychology, 95*(4), 752-760.

Rhee, E. Y., & Fiss, P. C. (2014). Framing controversial actions: Regulatory focus, source credibility, and stock market reaction to poison pill adoption. *Academy of Management Journal, 57*(6), 1734-1758.

Richards, D. A., & Schat, A. C. (2011). Attachment at (not to) work: applying attachment theory to explain individual behavior in organizations. *Journal of Applied Psychology, 96*(1), 169.

*Robbins, J. M., Ford, M. T., & Tetrick, L. E. (2012). Perceived unfairness and employee health: a meta-analytic integration. *Journal of Applied Psychology, 97*(2), 235-272.

*Saguy, T., & Kteily, N. (2011). Inside the Opponent's Head Perceived Losses in Group Position Predict Accuracy in Metaperceptions Between Groups. *Psychological Science, 22*(7), 951-958.

Salamon, S. D., & Robinson, S. L. (2008). Trust that binds: the impact of collective felt trust on organizational performance. *Journal of Applied Psychology, 93*(3), 593-601.

*Salvaggio, A. N., Schneider, B., Nishii, L. H., Mayer, D. M., Ramesh, A., & Lyon, J. S. (2007). Manager personality, manager service quality orientation, and service climate: test of a model. *Journal of Applied Psychology, 92*(6), 1741-1750.

Saparito, P. A., Chen, C. C., & Sapienza, H. J. (2004). The role of relational trust in bank–small firm relationships. *Academy of Management Journal, 47*(3), 400-410.

*Schaubroeck, J., Lam, S. S., & Cha, S. E. (2007). Embracing transformational leadership: team values and the impact of leader behavior on team performance. *Journal of Applied Psychology, 92*(4), 1020-1030.

*Schaubroeck, J., Lam, S. S., & Peng, A. C. (2011). Cognition-based and affect-based trust as mediators of leader behavior influences on team performance. *Journal of Applied Psychology, 96*(4), 863-871.

Schuelke, M.J, Day, E.A., McEntire, L.E., Boatman, P.R, Boatmman, J.E., Kowollik, V., & Wang, X. (2009). Relating indices of knowledge structure coherence and accuracy to skill-based performance: Is there utility in using a combination of indices? *Journal of Applied Psychology, 94*(4), 1076-1085.

Scott, B. A., & Judge, T. A. (2009). The popularity contest at work: who wins, why, and what do they receive?. *Journal of Applied Psychology, 94*(1), 20-33.

Shaffer, M.A., Harrison, D.A., Gregersen, H., Black, J.S., & Ferzandi, L.A. (2006). You can take it with you: Individual Differences and Expatriate Effectiveness. *Journal of Applied Psychology, 91*(1), 109-125.

Shapiro, D. L., Boss, A. D., Salas, S., Tangirala, S., & Von Glinow, M. A. (2011).

When are transgressing leaders punitively judged? An empirical test. *Journal of Applied Psychology, 96*(2), 412-422.

*Sherman, G. D., & Clore, G. L. (2009). The color of sin: White and black are perceptual symbols of moral purity and pollution. *Psychological Science, 20*(8), 1019-1025.

Simons, T., Friedman, R., Liu, L. A., & McLean Parks, J. (2007). Racial differences in sensitivity to behavioral integrity: attitudinal consequences, in-group effects, and" trickle down" among Black and non-Black employees. *Journal of Applied Psychology, 92*(3), 650-665.

*Simonton, D. K., & Song, A. V. (2009). Eminence, IQ, physical and mental health, and achievement domain: Cox's 282 geniuses revisited. *Psychological Science, 20*(4), 429-434.

*Sitzmann, T., Brown, K. G., Casper, W. J., Ely, K., & Zimmerman, R. D. (2008). A review and meta-analysis of the nomological network of trainee reactions. *Journal of Applied Psychology, 93*(2), 280-295.

Slaughter, J. E., Cable, D. M., & Turban, D. B. (2014). Changing job seekers' image perceptions during recruitment visits: the moderating role of belief confidence. *Journal of Applied Psychology, 99*(6), 1146-1158.

*Slaughter, J. E., Zickar, M. J., Highhouse, S., & Mohr, D. C. (2004). Personality trait inferences about organizations: development of a measure and assessment of construct validity. *Journal of Applied Psychology, 89*(1), 85-103.

Strauss, K., Griffin, M. A., & Parker, S. K. (2012). Future work selves: how salient hoped-for identities motivate proactive career behaviors. *Journal of Applied*

Psychology, 97(3), 580-598.

Summers, J. K., Humphrey, S. E., & Ferris, G. R. (2012). Team member change, flux in coordination, and performance: Effects of strategic core roles, information transfer, and cognitive ability. *Academy of Management Journal, 55*(2), 314-338.

*Sylvers, P. D., Brennan, P. A., & Lilienfeld, S. O. (2011). Psychopathic traits and preattentive threat processing in children: a novel test of the fearlessness hypothesis. *Psychological Science, 22*(10), 1280-1287.

Takeuchi, R., Lepak, D. P., Wang, H., & Takeuchi, K. (2007). An empirical examination of the mechanisms mediating between high-performance work systems and the performance of Japanese organizations. *Journal of Applied Psychology, 92*(4), 1069-1083.

Tay, C., Ang, S., & Van Dyne, L. (2006). Personality, biographical characteristics, and job interview success: a longitudinal study of the mediating effects of interviewing self-efficacy and the moderating effects of internal locus of causality. *Journal of Applied Psychology, 91*(2), 446-454.

Trevor, C. O., & Nyberg, A. J. (2008). Keeping your headcount when all about you are losing theirs: Downsizing, voluntary turnover rates, and the moderating role of HR practices. *Academy of Management Journal, 51*(2), 259-276.

van Hooft, E. A., & Noordzij, G. (2009). The effects of goal orientation on job search and reemployment: A field experiment among unemployed job seekers. *Journal of Applied Psychology, 94*(6), 1581-1590.

Van Hoye, G. & Lievens, Filip (2009). Tapping the grapevine: A closer look at word-of-mouth as a recruitment source. *Journal of Applied Psychology, 94*(2), 341-352.

Van Iddekinge, C.H., Putka, D.J., & Campbell, J.P. (2011). Reconsidering vocational interests for personnel selection: The validity of an interest-based selection test in relation to job knowledge, job performance, and continuance intentions. *Journal of Applied Psychology, 96*(1), 13-33.

Wallace, J. C., Popp, E., & Mondore, S. (2006). Safety climate as a mediator between foundation climates and occupational accidents: a group-level investigation. *Journal of applied psychology, 91*(3), 681-688.

Walters, B. A., Kroll, M., & Wright, P. (2010). The impact of TMT board member control and environment on post-IPO performance. *Academy of Management Journal, 53*(3), 572-595.

*Wanberg, C. R., Zhu, J., Kanfer, R., & Zhang, Z. (2012). After the pink slip: Applying dynamic motivation frameworks to the job search experience. *Academy of Management Journal, 55*(2), 261-284.

*Westphal, J. D., & Clement, M. B. (2008). Sociopolitical dynamics in relations between top managers and security analysts: Favor rendering, reciprocity, and analyst stock recommendations. *Academy of Management Journal, 51*(5), 873-897.

*Wisneski, D. C., Lytle, B. L., & Skitka, L. J. (2009). Gut reactions: Moral conviction, religiosity, and trust in authority. *Psychological Science, 20*(9), 1059-1063.

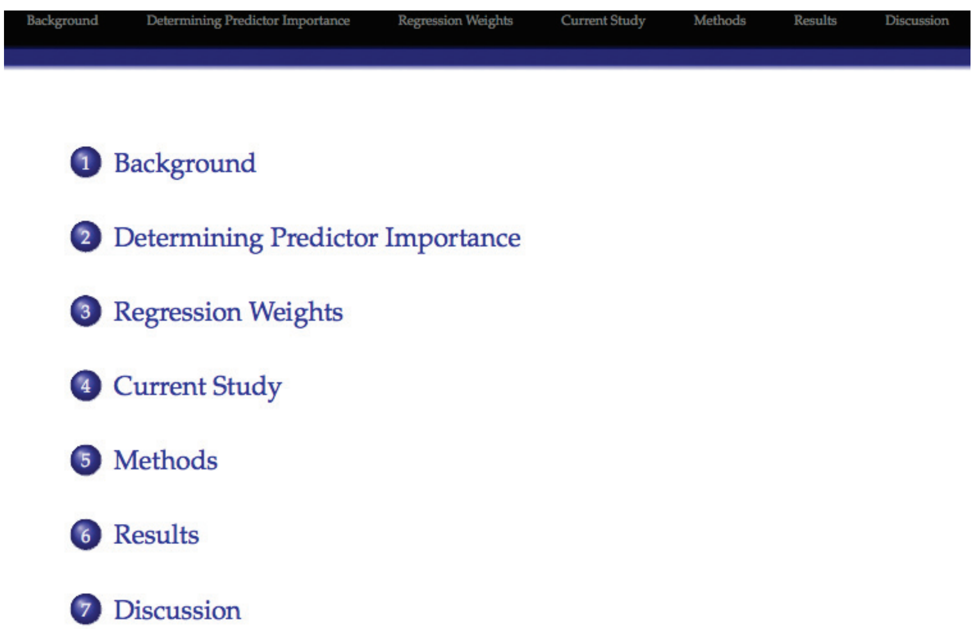
+Wong, K. F. E., & Kwong, J. Y. (2007). The role of anticipated regret in escalation of commitment. *Journal of Applied Psychology, 92*(2), 545-554.

Zhang, Z., & Peterson, S. J. (2011). Advice networks in teams: The role of transformational leadership and members' core self-evaluations. *Journal of Applied Psychology, 96*(5), 10041017.

*Yang, L. Q., Bauer, J., Johnson, R. E., Groer, M. W., & Salomon, K. (2014). Physiological mechanisms that underlie the effects of interactional unfairness on deviant behavior: The role of cortisol activity. *Journal of Applied Psychology*, 99(2), 310-321.

*Zhao, H., & Seibert, S. E. (2006). The big five personality dimensions and entrepreneurial status: a meta-analytical review. *Journal of Applied Psychology, 91*(2), 259-271.

Appendix B: Final Dissertation Defense Slides



Linear Regression

- Regression is used to create linear combinations of predictor variables that minimize SSE in predicting an outcome variable of interest.
- The general model is:

$$y = b_0 + b_1x_1 + b_2x_2 + \ldots + b_px_p + e$$

- When scores on the predictor and outcome variable are converted to z-scores the regression equation can be presented in the following matrix form:

$$\hat{y} = \mathbf{X}\hat{\beta}$$

- For simplicity $\hat{\beta}$ will be represented as β and refer to standardized regression coefficients for the rest of this presentation

Regression in I/O

- The I/O literature has used regression to examine a variety of topics including:
  - Determining valid predictors of job performance (e.g., Schmidt & Hunter, 1998).
  - Examining predictors of leadership emergence and effectiveness (e.g., Judge, Bono, Ilies, & Gerhardt, 2002).
  - Validity of predictors across the lifespan (e.g., Lievens, Ones, & Dilchert, 2009).
- Regression is also used in applied I/O settings:
  - Developing and evaluating selection systems.
  - Evaluating intervention programs.
  - Determining drivers of employee engagement.

Background | Determining Predictor Importance | Regression Weights | Current Study | Methods | Results | Discussion

Predictor Importance

- Interpreting regression weights becomes difficult in the presence of correlated predictors.
- Researchers have used various methods to evaluate the relative importance of predictors used in regression.

Background | Determining Predictor Importance | Regression Weights | Current Study | Methods | Results | Discussion

Defining Importance

How can we think about importance (LeBreton, Ployhart, & Ladd, 2004)?

- Direct Effects: The contribution of the predictor to the outcome variable without consideration for other predictors.
- Partial Effects: A predictor's contribution when accounting for some type of model subset(s).
- Total Effects: The contribution of a predictor to the outcome variable after the contributions of all other predictors have been removed.

Zero-Order Correlation Coefficients

- Measure of direct effects.
- Correlation between a single predictor variable and the outcome variable:

$$r_{y\boldsymbol{x}_i} = \frac{cov(\boldsymbol{y}, \boldsymbol{x}_i)}{s_y s_{\boldsymbol{x}_i}}.$$

- When the predictors are uncorrelated:

$$\sum_{i=1}^{p} r_{y\boldsymbol{x}_i}^2 = R^2.$$

Standardized Regression Weights

- Measure of total effects.
- Weights obtained from OLS regression when the scores on the predictor and criterion are converted to z-scores.

$$\boldsymbol{\beta} = (\mathbf{X}_z'\mathbf{X}_z)^{-1}\mathbf{X}_z'\boldsymbol{y}_z$$

$$\boldsymbol{\beta} = \boldsymbol{R}_X^{-1}\boldsymbol{r}_{Xy}$$

- When the predictors are uncorrelated:

$$\sum_{i=1}^{p} \beta_i^2 = R^2.$$

Structure Coefficients

- Measure of direct effects.
- A structure coefficient is the correlation between a predictor score and $\hat{y}$:

$$r_{S_i} = r_{\hat{y}x_i}.$$

Pratt Measure

- Measure of direct and total effects.
- Product of the standardized regression weight and the zero-order correlation coefficient:

$$m_i = \beta_i r_{yx_i}.$$

- Even when predictors are correlated the following holds:

$$\sum_{i=1}^{p} m_i = R^2$$

Commonality Analysis

- A measure of total effects.
- Partitions the variance explained by the model into unique and common effects.

Background Determining Predictor Importance Regression Weights Current Study Methods Results Discussion

Commonality Analysis

- Unique effects are calculated by squaring a predictor's semipartial correlation with the criterion:

$$u_i = R^2_{model} - R^2_{model-i}.$$

- Common effects measure a predictor's contribution that the predictor shares with every possible predictor set.
- There are $2^p - 1$ commonality coefficients associated with each model.

Background | **Determining Predictor Importance** | Regression Weights | Current Study | Methods | Results | Discussion

Dominance Analysis

- Measures direct, total, and partial effects.
- Compares pairs of predictors and how they behave in $h = 2^{(p-2)}$ models.
- General Dominance weights are an average of conditional dominance weights associated with each predictor.

Background | **Determining Predictor Importance** | Regression Weights | Current Study | Methods | Results | Discussion

Relative Weights

- A measure of total effects.
- Finds the best-fitting set of orthogonal variables, $\boldsymbol{Z}$.
  - SSE between $\boldsymbol{X}$ and $\boldsymbol{Z}$ is minimized.
- The relative weights, $\boldsymbol{\varepsilon}$, are a product of the squared regression weights from regressing $\boldsymbol{y}$ on the columns of $\boldsymbol{Z}$ and the squared regression weights from regressing each $\boldsymbol{x}_i$ on the corresponding $\boldsymbol{z}_i$.
- $\sum_{i=1}^{p} \varepsilon_i^2 = R^2$

Comparison of Relative Importance Analyses

- There has been interest, but not a comprehensive examination of the level of agreement between the different methods of relative importance analyses.
- LeBreton et al. (2004) performed a Monte Carlo simulation
  - Used the rankings produced by dominance analysis and calculated a Kendall's τ for the agreement of these rankings, with rankings based on squared zero-order correlations, squared beta coefficients, the Pratt measure, and relative weights analysis.
  - Correlations ranged from .78 (squared beta) to .96 (relative weights).
  - Did not provide a full correlation matrix for the relative importance measures and only dominance analysis was correlated with all alternative methods examined.

Regression Weights

- Regression research has also focused on the performance of regression weights in different contexts.
- Optimal weights capitalize on sample characteristics that may not be representative of the larger population and have occurred due to sampling error.
  - This can lead to issues with cross-validation.
- One vein of research focuses on the performance of optimal weights when compared with unit weights.

Unit Weights

- Unit weights (Wainer, 1976; Wainer, 1978; Raju, Bilgic, Edwards, & Fleer, 1999):
    - Do not capitalize on sampling error.
    - Are not sensitive to outliers.
    - They can perform similarly or better than optimal weights in cross-validation.

Parameter Sensitivity in Regression

- Parameter sensitivity is determined by examining how changes in weights are related to changes in fit indices (e.g., SSE and R^2 values).
- Sensitive weights are characterized by a large change in fit indices accompanied by small changes in the weights.
- Fit indices associated with insensitive weights are robust to slight (and sometimes not so slight) changes in weights.

Fungible Weights

- Waller (2008) proposed a method of evaluating model sensitivity.
- When a regression equation has 3 or more predictors an infinite number of alternative weight vectors can be found that will produce an R^2 slightly lower than the optimal R^2.
- The procedure for obtaining these alternative weight vectors requires the correlation matrix of predictors and the criterion.
  - The results do not rely on sample size.
  - Uncorrelated predictors still result in an infinite set of alternative weights.

Research Questions

Question 1: How is regression used in I/O and general psychology and how are regression weights interpreted?
Question 2: What analyses have been used in the I/O and general psychology literature to interpret beta weights in regression?
Question 3: Are regression models in the I/O and general psychology literature insensitive to shifts in predictor weights?
Question 4: How influential are the I/O and general psychology articles that use OLS regression?

Background | Determining Predictor Importance | Regression Weights | Current Study | **Methods** | Results | Discussion

Database of Past Literature

- Reviewed articles published in *Journal of Applied Psychology* 2003 through 2014, as well as articles from alternating years of *Psychological Science* and *Academy of Management Journal* (AMJ) (specifically 2003, 2005, 2007, 2009, 2011, and 2013 in *Psychological Science* and 2004, 2006, 2008, 2010, 2012, and 2014 in AMJ).
- Inclusion criteria:
    - OLS regression with 3 or more predictors.
        - No interaction terms.
        - No exponent terms.
    - Regression coefficients or results from one of the relative importance analyses must be displayed.
    - The most inclusive model in hierarchical regressions were used.

Background | Determining Predictor Importance | Regression Weights | Current Study | **Methods** | Results | Discussion

Database of Past Literature

Articles coded for:

- Whether a full correlation matrix of predictors and the criterion is present
- Authors' country affiliations
- Regression topic
- Number of predictors
- Primary or meta-analytic data
- Sample size used in regression
- Conclusions drawn from regression
- Relative importance analysis used
- Whether R^2_{adj} was displayed
- Number of times article had been cited according Google Scholar as of February 24, 2017

Background Determining Predictor Importance Regression Weights Current Study **Methods** Results Discussion

Relative Importance Analysis

- Relative importance analyses were conducted for every regression which meets inclusion criteria and had a complete, positive definite correlation matrix.
- Rank ordering of predictors were recorded based on the magnitude of:
  - Standardized regression weights ($\boldsymbol{\beta}$)
  - Zero-order correlations ($\boldsymbol{r_{yx}}$)
  - Squared Structure Coefficients ($\boldsymbol{r_S^2}$)
  - Unique Coefficients from commonality analysis (U)
  - Sum of Common Coefficients from commonality analysis (C)
  - General Dominance Weights (GD)
  - Pratt Measure ($\boldsymbol{m}$)
  - Relative Weights ($\boldsymbol{\varepsilon}$)

Background Determining Predictor Importance Regression Weights Current Study **Methods** Results Discussion

Relative Importance Analysis

- For each regression relative importance agreement metrics included:
  - An intraclass correlation among the rank-orderings produced for each regression.
  - Kendall's τ correlations between all pairs of rank orders.

Sensitivity Analysis

- All regressions that went through relative importance analysis were also included in the sensitivity analysis.
- Using the Fungible weights procedure from Waller (2008), 5,000 alternative weight vectors were produced for each condition:
  - 0.01 reduction: $R_a^2 = R_\beta^2 - 0.01$
  - 1% reduction: $R_a^2 = R_\beta^2 * 0.99$
- The R^2 produced by using unit weights was also examined.
  - For $r_{yx_i} > 0$ the unit weight was set to 1.
  - For $r_{yx_i} < 0$ the unit weight was set to -1.
  - The model R^2 for the unit weights was calculated according to Dana and Dawes (2004):

$$R_U^2 = \frac{(\boldsymbol{\beta}'_U \boldsymbol{r}_y \mathbf{x})^2}{\boldsymbol{\beta}'_U \mathbf{R}_x \boldsymbol{\beta}_U}.$$

Simulation Study

- Compare results of fungible weights analyses to results for similar models.
- Selected 5 studies for further analysis:
  - Top 3 most highly cited articles that drew conclusions based on the size of the beta weights and contained full, positive definite correlation matrices.
  - The top 2 most highly cited articles that conducted at least one relative importance analysis and contained full, positive definite, correlation matrices.

Simulation Study

- Used fungibleR (Waller, 2016) to produce 1000 positive definite predictor correlation matrices that satisfied:

$$\beta^T \mathbf{R}_X^* \beta = R^2.$$

- Each of the 1000 $\mathbf{R}_X^*$ were put through the fungible weights analysis using the β from the published study and reducing R^2 by 0.01.
- For comparison sake, each of the original $\mathbf{R}_X$ was put through the same analysis 1000 times.

Database Summary

- 197 articles were found that fit the inclusion criteria.
  - 409 regressions were pulled from articles that contained a full correlation matrix.
    - 7 regressions were removed due to a lack of a positive definite $\mathbf{R}_X$

Article Characteristic	Count	Percent
JAP	123	62.44%
AMJ	45	22.84%
Psychological Science	29	14.72%
Hierarchical Regression	99	50.25%
Meta Analysis	20	10.15%
Full Correlation Matrix	117	59.39%
Interpreted Coefficient Sign	126	63.96%
Interpreted Coefficient Size	15	7.61%
Interpreted Coefficient Significance	173	87.82%
Interpreted R^2	76	38.58%
Conducted Relative Importance Analysis	9	4.57%
Reported Adjusted R^2	60	30.46%

Background Determining Predictor Importance Regression Weights Current Study Methods **Results** Discussion

Database Summary: Author Country Affiliation

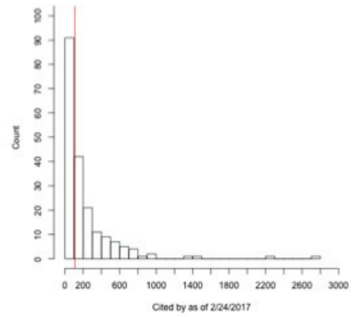
Country	Number of Articles with Authors Affiliated with Country	Percent of Total Articles
US	166	84.26%
Hong Kong	13	6.60%
Netherlands	13	6.60%
UK	13	6.60%
Australia	8	4.06%
Canada	8	4.06%
Belgium	4	2.03%
France	4	2.03%
Singapore	4	2.03%
South Korea	4	2.03%
Germany	3	1.52%
Israel	2	1.02%
Switzerland	2	1.02%
India	1	0.51%
Italy	1	0.51%
Japan	1	0.51%
Philippines	1	0.51%
Portugal	1	0.51%
Spain	1	0.51%
Sweden	1	0.51%
Taiwan	1	0.51%

Background Determining Predictor Importance Regression Weights Current Study Methods **Results** Discussion

Database Summary: Number of Articles by Topic Area

Topic	Article Count	Percent of Total Articles
Predictors of performance	50	25.38%
Work motivation and attitudes	40	20.30%
Work groups-teams	30	15.23%
Leader influences	21	10.66%
Societal issues	13	6.60%
Training and development	5	2.54%
Consumer behavior	5	2.54%
Decision making	4	2.03%
Performance measurement	4	2.03%
Career issues	3	1.52%
Developmental psychology	3	1.52%
Human factors	3	1.52%
Neuropsychology	3	1.52%
Reward systems	3	1.52%
Adult psychology	3	1.52%
Health psychology	2	1.02%
Research methodology	2	1.02%
Clinical interventions	1	0.51%
Psychopathology	1	0.51%
Other	1	0.51%

Number of Times Each Article Was Cited as of February 24, 2017



The red vertical line indicates the *median* (108). $Mean = 223.20$, $SD = 328.79$, 1^{st} $Quartile = 51$, 3^{rd} $Quartile = 248$, $n = 197$.

Background Determining Predictor Importance Regression Weights Current Study Methods **Results** Discussion

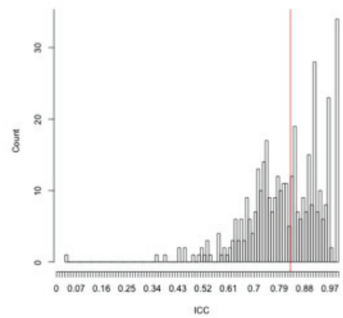
Summary Metrics for Reression with a Full Correlation Matrix

Metric	n	*Mean*	*Median*	*SD*	*Min*	*Max*	*Q1*	*Q3*
Number of predictors	409	6.970	6.000	3.920	3.000	25.000	4.000	9.000
Sample Size	409	385.900	147.000	822.791	27.000	8839.000	85.500	288.500
κ	402	2.744	2.408	1.273	1.110	11.290	1.874	3.345
OLS R^2	402	0.284	0.258	0.196	0.000	0.835	0.127	0.414
Wherry (1931) R^2_{adj}	402	0.246	0.214	0.197	-0.110	0.082	0.082	0.368

Background Determining Predictor Importance Regression Weights Current Study Methods **Results** Discussion

Relative Importance Analysis

ICC for Relative Importance Metrics from 402 Regressions



The red vertical line indicates the *median* (0.83). *Mean* = 0.81, *SD* = 0.13, 1^{st} *Quartile* = 0.73, 3^{rd} *Quartile* = 0.91, *n* = 402.

Background Determining Predictor Importance Regression Weights Current Study Methods **Results** Discussion

Relative Importance Analysis

Average τ correlations across 402 regressions with *SD* below

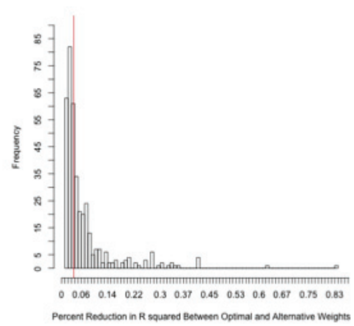
	β_i	r_{yx_i}	GD	ε	r_s^2	U	C	m
β	1.00							
r_{yx}	0.58	1.00						
	0.31							
GD	0.72	0.82	1.00					
	0.24	0.20						
ε	0.72	0.81	0.97	1.00				
	0.25	0.20	0.07					
r_s^2	0.58	1.00	0.82	0.81	1.00			
	0.31	0.00	0.20	0.20				
U	0.90	0.58	0.75	0.74	0.58	1.00		
	0.17	0.30	0.23	0.23	0.30			
C	0.41	0.60	0.60	0.59	0.61	0.42	1.00	
	0.36	0.34	0.33	0.34	0.34	0.36		
m	0.78	0.78	0.86	0.86	0.78	0.78	0.51	1.00
	0.82	0.22	0.17	0.17	0.22	0.21	0.34	

Sensitivity Analysis

- Using the Fungible weights procedure from Waller (2008) 5,000 alternative weight vectors were produced for each regression for two conditions:
  - 0.01 reduction: $R_a^2 = R_\beta^2 - 0.01$ ($n = 387$).
  - 1% reduction: $R_a^2 = R_\beta^2 * 0.99$ ($n = 402$).
- Metrics of interest:
  - Number of alternative weight vectors, out of 5000, preserve the entire original rank order of the predictors according to the original $\boldsymbol{\beta}$.
  - Number of alternative weight vectors, out of 5000, associate the top ranked coefficient with the same variable as the original $\boldsymbol{\beta}$.
  - Kendall's τ between the rank order of predictors according to the original $\boldsymbol{\beta}$ and rank order according to each alternative weight vector.

Sensitivity Analysis: Reduction in R^2

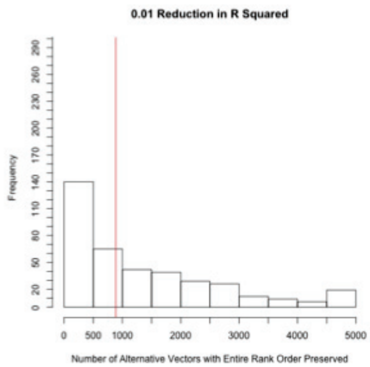
Percent Reduction of R^2 Between Optimal and Alternative Models
When Reducing R^2 by 0.01



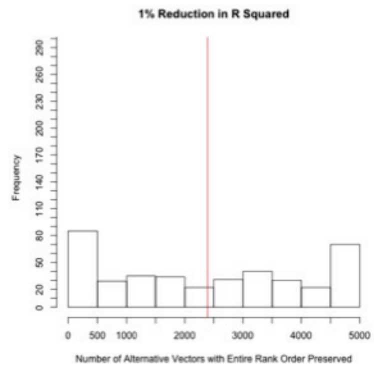
The red vertical line indicates the *median* (3.68%). *Mean* = 6.93%, *SD* = 8.89%, 1st *Quartile* = 2.34%, 3rd *Quartile* = 7.58%, $n = 387$.

Background Determining Predictor Importance Regression Weights Current Study Methods **Results** Discussion

Sensitivity Analysis: Agreement on Full Rank Order



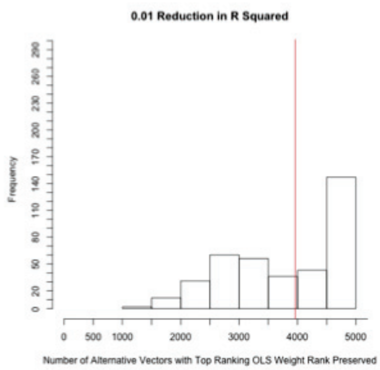
The red vertical line indicates the *median* (887).
$Mean = 1323.30$, $SD = 1355.41$, 1^{st} *Quartile* = 158.00, 3^{rd} *Quartile* = 2053.00, $n = 387$.



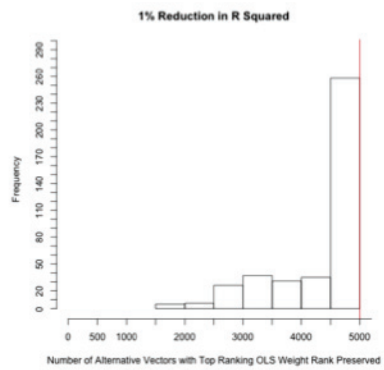
The red vertical line indicates the *median* (2389.00).
$Mean = 2392.49$, $SD = 1728.97$, 1^{st} *Quartile* = 847.50, 3^{rd} *Quartile* = 3859.75, $n = 402$.

Background Determining Predictor Importance Regression Weights Current Study Methods **Results** Discussion

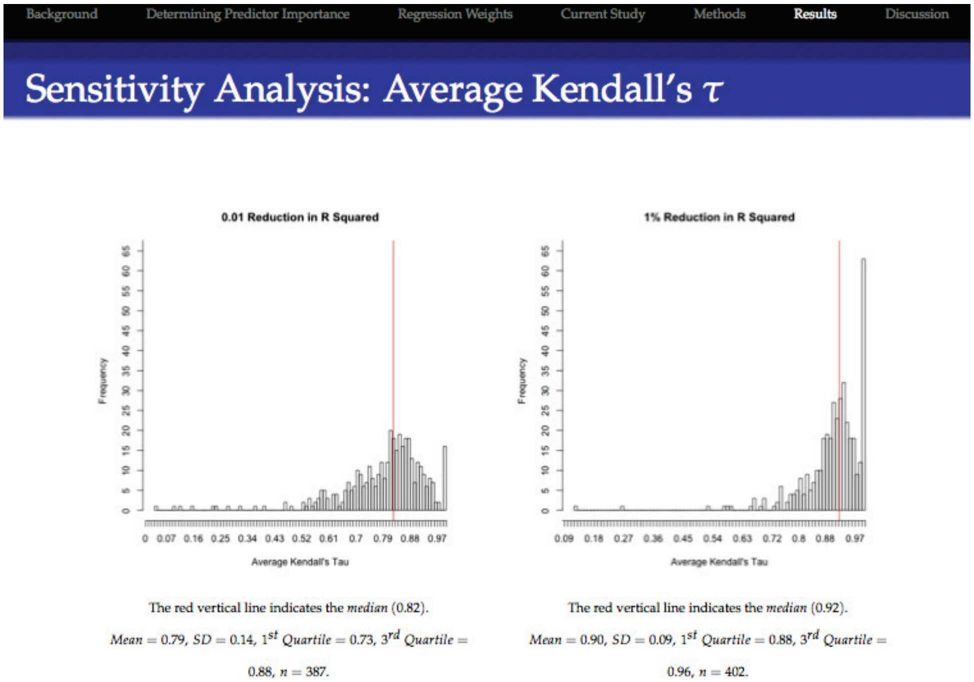
Sensitivity Analysis: Agreement on Top Ranked Predictor

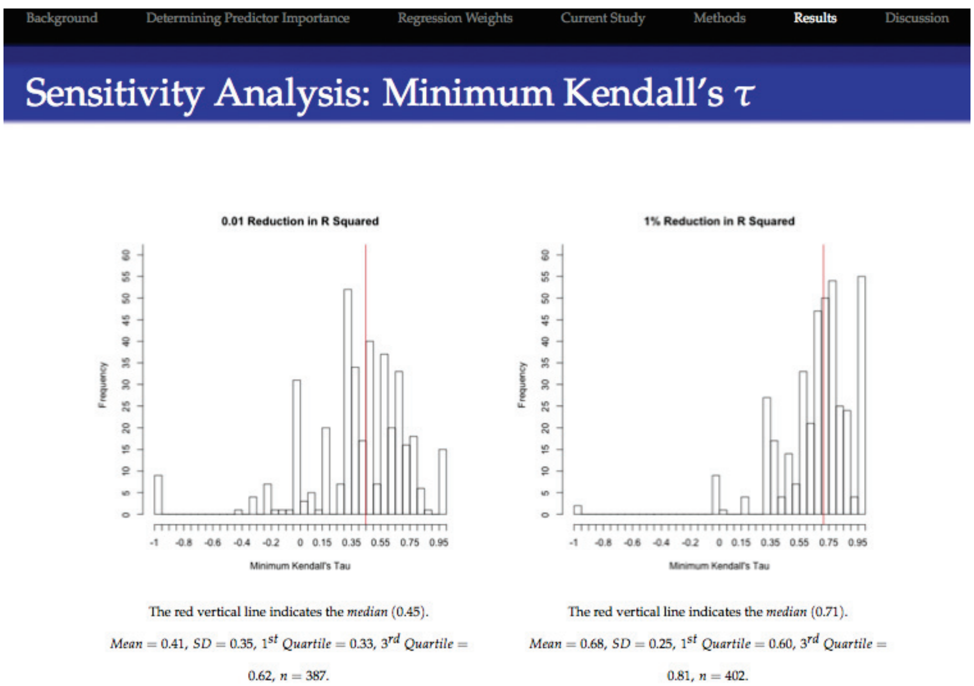


The red vertical line indicates the *median* (3961.00).
$Mean = 3835.68$, $SD = 1049.35$, 1^{st} *Quartile* = 2907.50, 3^{rd} *Quartile* = 4993.00, $n = 387$.



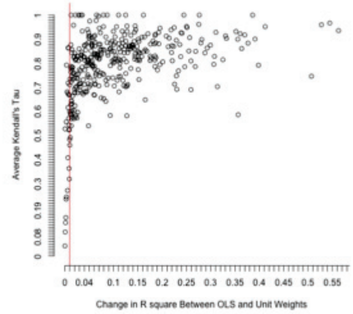
The red vertical line indicates the *median* (5000.00).
$Mean = 4422.57$, $SD = 842.25$, 1^{st} *Quartile* = 3921.25, 3^{rd} *Quartile* = 4993.00, $n = 402$.


Background Determining Predictor Importance Regression Weights Current Study Methods Results Discussion
Sensitivity Analysis: Average Kendall's τ
0.01 Reduction in R Squared
1% Reduction in R Squared
Frequency
Average Kendall's Tau
The red vertical line indicates the median (0.82).
Mean = 0.79, SD = 0.14, 1st Quartile = 0.73, 3rd Quartile = 0.88, n = 387.
The red vertical line indicates the median (0.92).
Mean = 0.90, SD = 0.09, 1st Quartile = 0.88, 3rd Quartile = 0.96, n = 402.


Background Determining Predictor Importance Regression Weights Current Study Methods Results Discussion
Sensitivity Analysis: Minimum Kendall's τ
0.01 Reduction in R Squared
1% Reduction in R Squared
Frequency
Minimum Kendall's Tau
The red vertical line indicates the median (0.45).
Mean = 0.41, SD = 0.35, 1st Quartile = 0.33, 3rd Quartile = 0.62, n = 387.
The red vertical line indicates the median (0.71).
Mean = 0.68, SD = 0.25, 1st Quartile = 0.60, 3rd Quartile = 0.81, n = 402.

Unit Weights and Sensitivity

If the model R^2 does not change much when using equal weights does that mean the model is insensitive to weight changes?
If the model R^2 changes a lot when using equal weights does that mean the model is sensitive to weight changes?



The red vertical line is placed at 0.01 since the average τ was taken from the $R^2_a = R^2_\beta - 0.01$ sensitivity analysis. $n = 387$.

Background Determining Predictor Importance Regression Weights Current Study Methods Results Discussion

Simulation Study

- You can evaluate a model's sensitivity in isolation using fungible weights.
- You may want to compare your model to other "similar" models.
- For this study similar models held the following constant:
  - R^2
  - β
- The correlations were allowed to vary.

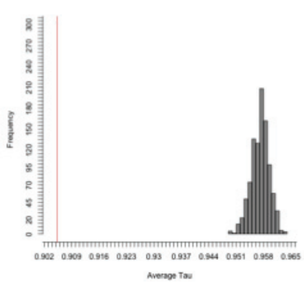
Simulation: Dabos and Rousseau (2004)

- Studied how mutuality and reciprocity in psychological contracts was related to performance outcomes.
- Regressed scientists' perceptions of director transactional obligations onto director perception of director transactional obligations, director perception of director relational obligations, and director perception of director balanced obligations.
- Used regression coefficients to identify "strongest predictor".
- Cited 516 times as of February 24, 2017.

Background Determining Predictor Importance Regression Weights Current Study Methods **Results** Discussion

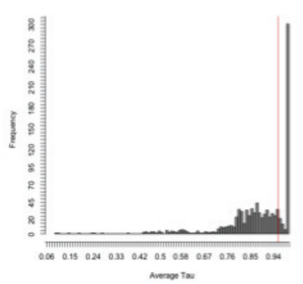
Simulation: Dabos and Rousseau (2004)

Fungible Weights Distribution: 1000 Fungible Weights Analyses on R_X



Red line indicates median average τ from running fungible weights on 1000 R_X^*. $Mean = 0.957$, $median = 0.957$, $SD = 0.002$, 1^{st} $Quartile = 0.956$, 3^{rd} $Quartile = 0.959$, $n = 1000$.

Fungible R Distribution:1000 R_X^* Put Through Fungible Weights



Red line indicates median average τ from running fungible weights on original R_X 1000 times, 64.50% fall below the red line. $Mean = 0.881$, $median = 0.905$, $SD = 0.135$, 1^{st} $Quartile = 0.823$, 3^{rd} $Quartile = 0.959$, $n = 1000$.

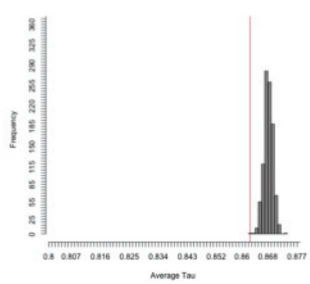
Simulation: Mumford, Van Iddekinge, Morgeson, and Campion (2008)

- Study focused on the development and validity of a situational judgement test (SJT) for team role knowledge called the Team Role Test (TRT).
- Regressed task role performance onto mental ability, agreeableness, conscientiousness, emotional stability, extraversion, openness, and overall TRT.
- Used regression coefficients to identify "strongest predictor".
- Cited 102 times as of February 24, 2017.

Background Determining Predictor Importance Regression Weights Current Study Methods **Results** Discussion

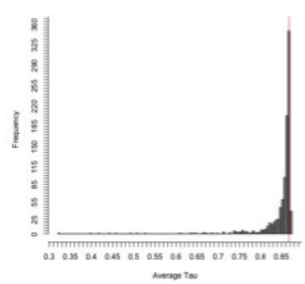
Simulation: Mumford et al. (2008)

Fungible Weights Distribution: 1000 Fungible Weights Analyses on R_X



Red line indicates median average τ from running fungible weights on 1000 R_X^*. $Mean = 0.957$, $median = 0.957$, $SD = 0.002$, 1^{st} $Quartile = 0.956$, 3^{rd} $Quartile = 0.959$, $n = 1000$.

Fungible R Distribution:1000 R_X^* Put Through Fungible Weights



Red line indicates median average τ from running fungible weights on original R_X 1000 times, 84.17% fall below the red line. $Mean = 0.842$, $median = 0.862$, $SD = 0.050$, 1^{st} $Quartile = 0.850$, 3^{rd} $Quartile = 0.867$, $n = 1000$.

Summary of Results

- Articles that use regression are highly influential.
- Regression is used across a variety of topic areas.
- Relatively few articles that use regression draw conclusions based on values of the regression weights.
  - However it still happens, and in highly regarded publications.
- A shocking number of articles that use regression do not include full correlation matrices.

Background | Determining Predictor Importance | Regression Weights | Current Study | Methods | Results | **Discussion**

Summary of Results

- Using different relative importance metrics can lead to different conclusions.
- None of the relative importance metrics examined in this study agreed on rank-ordering of variables 100% of the time.

Summary of Results

- The fungible weights analysis revealed that very few models maintained the original rank ordering of predictors across all alternative vectors.
  - There was still notable disagreement between original and alternative weight vectors on which variable was associated with the top ranked weight.
- There was variation across the models included in the study in how sensitive the model was to shifts in regression weights.
- The simulation demonstrated one method of comparing a model's sensitivity to similar models' sensitivity.
  - It also demonstrated that even when models have the same R^2 and β their sensitivity to changes in weights can differ.

Background Determining Predictor Importance Regression Weights Current Study Methods Results **Discussion**

Recommendations: Questions to Ask

- Have I designed my study well?
- What question am I trying to answer with my study?
- Do I want a model that is going to do well in my current sample or one that I can successfully apply to new samples?
- Am I going to try make a statement regarding what is important in my model? If so, what do I mean by importance?
- Is my model sensitive to changes in weights?

Background Determining Predictor Importance Regression Weights Current Study Methods Results **Discussion**

Recommendations: Ways to Improve Published Studies

1. Do not draw conclusions based solely on the size of the β_i's.
2. Always provide full correlation or covariance matrices for all variables used in a regression model.

Background Determining Predictor Importance Regression Weights Current Study Methods Results **Discussion**

Questions?

Appendix C: Sarah Semmel's C.V.

Curriculum Vitae
Sarah Glazer Semmel
June 2017

Personal Information
San Francisco, CA
sgsemmel@gmail.com
Computer literate in R, SAS, SPSS, STATA, SQL; Excel, Power Point, Access, Word
Basic knowledge of written and spoken Spanish and Yiddish

Education
Ph.D. Industrial/Organizational Psychology, Concentration in Quantitative Psychology
Advisor Deniz S. Ones, University of Minnesota, 2017
G.P.A. 3.9
B.S. Psychology, Minor Statistics, Magna Cum Laude
University of Maryland, May 2009
G.P.A. 3.96

Honors and Awards
University of Minnesota
Finalist, John Flanagan Award for the Outstanding Student Contribution to the 2014 SIOP Conference Program
Top Poster, 2014 SIOP Conference Program
Graduate Research Partnership Program, Summer 2011
University of Minnesota Graduate School Fellowship, 2010-2011
University of Maryland
Dean's Academic Scholar, 2009
Senior Marshall, 2009
Philip Merrill Presidential Scholar, 2008-2009
Gemstone and Honors Programs, 2005-2009
Distinguished Dean's List of Outstanding Students, 2005-2009
Primannum Honor Society Jo Anne J. Trow Chapter Leadership Award and Scholarship, 2007

Research Experience
Ph.D. Candidate, Department of Psychology, University of Minnesota, Minneapolis, Minnesota, 2010-2017.
Conducting dissertation research on how to accurately interpret beta weights produced in linear regression and how the misinterpretation of these weights has affected the I/O literature. Created a system to enable and promote knowledge-sharing among current, past, and future I/O students.

Researcher, College Board Team, Department of Psychology, University of Minnesota, Minneapolis, Minnesota, 2013-2014.

Analyze a large, multi-year, multi-institution dataset focused on individuals' college performance. Project focused on what factors lead undergraduates to become a psychology major. Collaborated with team members to design, implement, and interpret various analyses across a range of projects. Established a protocol for tracking projects and archiving project-relevant information to facilitate team onboarding and collaboration.

Researcher, Green Team, Department of Psychology, University of Minnesota, Minneapolis, Minnesota. 2010-2012.

Member of a research team focused on understanding and increasing environmentally friendly behavior in the workplace. Used meta-analytic tools to examine effective workplace interventions and produced a first-authored poster presentation. Assisted other team members in conference preparation and publication submission.

Research Assistant, Center for Autism and Related Disorders, Kennedy Krieger Institute, Baltimore, Maryland. 2009-2010.

As a member of an interdisciplinary team, provided services that facilitated and supported multiple research protocols: analyzed data and reported preliminary findings; completed informed consent procedures; provided developmentally appropriate child care; participated in research team and scholarly meetings; and prepared and stored blood samples.

Research Team Member, Gemstone Program, University of Maryland, College Park, Maryland. 2005-2009.

As part of a highly selective, interdisciplinary student team, designed, directed and conducted original research using a public use data set. Using SPSS, analyzed data to identify trends and relationships among teen risk behaviors. Wrote and successfully defended thesis to a panel of external experts.

Research Intern, Department of Psychiatry, School of Medicine, University of Maryland, Baltimore, Maryland. 2007-2008.

Using Stata, analyzed public use data set describing ambulatory care psychiatric patients. Identified and summarized trends, developed tables and graphic representations, and proposed hypotheses for further testing. Collaborated with colleagues to write and submit an article to peer-reviewed journals.

Research Assistant, Department of Psychology, University of Maryland, College Park, Maryland. 2006-2007.

Worked independently and as a team member in an interpersonal relationships research laboratory. Developed literature reviews and annotated bibliographies. Assisted in the design and implementation research projects. Recruited and ran subjects. Used SPSS to record and analyze data.

Applied Experience

People Scientist, Twitter, San Francisco, California, 2016-present.

Design, execute, and analyze results of research studies to answer questions about the Twitter workforce. Project topics include selection measures, performance management, competency modeling, and employee engagement.

People Research Scientist Contractor, Facebook, Menlo Park, California, 2015-2016.
Answer complex questions regarding the Facebook workforce by designing original research and analyzing existing data sets. Projects focus on training evaluation, selection system design and evaluation, and employee engagement. Communicate findings, and make recommendations to stakeholders throughout the organization.

Consulting Intern, Personnel Decisions Research International, Minneapolis, Minnesota, 2011-2015.
Assist with various consulting projects for public and private sector clients related to job analysis, competency modeling, leadership development, assessment development, and assessment validation. Conduct literature reviews, code and analyze data, prepare findings for presentation, and draft tech reports.

Talent Assessment Intern, Amazon, Seattle, Washington, Summer 2013.
Designed and managed a validation study using 400 interns and their managers. Collaborated with subject matter experts to develop and evaluate selection tools for technical jobs. Analyzed assessment data to determine validity, adverse impact, and aid in scale construction. Presented findings and recommendations for practice to members of the executive team.

Resident Assistant, Department of Resident Life, University of Maryland, College Park, Maryland. 2006-2009.
Provided crisis intervention, guidance and support to undergraduate students living in campus housing. Developed and implemented community service, social and recreational programs.

Crisis Line Volunteer Counselor, Help Center, University of Maryland, College Park, Maryland. 2006-2009.
Provided crisis intervention, and information and referral services to callers presenting with a wide range of emotional needs. Served as a mentor to new volunteers. As Co-Director of External Public Relations, developed and led outreach activities.

Child Clinician, Children's Development Clinic, Prince Georges Community College and University of Maryland, College Park, Maryland. 2006, 2008.
Provided physically and socially stimulating, individual and group experiences to developmentally challenged preschool children. Developed individualized treatment plans. Provided support and encouragement to parents.

Teaching Experience

Section Leader, Department of Psychology, University of Minnesota, Minneapolis, Minnesota. 2011-present.
Lead lab sections once a week for *Introduction to Psychological Measurement and Data Analysis* and *Research Methods.* Hold weekly office hours, and respond to student questions and concerns. Create lab activities, exam and homework questions.

Teaching Assistant, Department of Psychology, University of Minnesota, Minneapolis, Minnesota. 2010-2011.
Serve as graduate teaching assistant for *Introduction to Industrial and Organizational Psychology*. Hold weekly office hours, and respond to student questions and concerns. Create exam questions. Attend and assist during lectures.

Publications and Presentations

Semmel, S., Jones, J. & Goebl, A. (2017). What is Machine Learning? Foundations and Introduction Useful Methods. Presented at the 32nd Annual Conference of the Society for Industrial Organizational Psychology.

Jones, J., Goebl, A. & Semmel, S. (2017). Modern Methods for I-O Psychologist: An Interactive Tutorial in R. Presented at the 32nd Annual Conference of the Society for Industrial Organizational Psychology.

Ott-Holland, C., Pearce, M., Stanek, K., Robinson, R., Semmel, S. & Sims, C. (2017). Communicating Our Value as I-O Practitioners. Presented at the 32nd Annual Conference of the Society for Industrial Organizational Psychology.

Jones, J., Goebl, A. & Semmel, S. (2016). Handling Big(gish) Data in R: An Introductory Interactive Tutorial. Presented at the 31st Annual Conference of the Society for Industrial Organizational Psychology.

Semmel, S. & Ones, D.S. (2014). Misleading influence in I/O: Insensitive standardized weights in OLS regression. Presented at the 29th Annual Conference of the Society for Industrial Organizational Psychology.

Zorzie, M., Ferstl, K., Horgen, K., & Semmel, S. (2014). *Performance and Development Research for* [*client redacted*]: *2014 Survey of Managers, Directors, and VPs.* (Technical Report #818). Minneapolis: Personnel Decisions Research Institutes, Inc.

Sanderson, K., Klein, R., Semmel, S., & Mueller-Hanson, R. (2013). Career accelerators: Competencies essential to leader transitions in the government. Presented at the IPAC Conference.

Bruskiewicz, K.T., Stewart, R.W., Semmel, S., David, N., & Ohland, K. (2012). *Job Analysis, Development, and Content-Validation of Job Qualifications and Interview Guides for CSSR/CSSR (SAFE) Positions at* [*client redacted*](Technical Report #737). Arlington, Virginia: PDRI, an SHL Company.

Personnel Decisions Research Institute (2012). *Development of PDRI's COTS Leadership Competency Model: Background and Meta-analysis* (Institute Report #767). Arlington, VA: PDRI, a CEB Company. (Contributors: Carrick, C., Klein, R., Sanderson, K., Semmel, S., Stellmack, A., & Mueller-Hanson, R.)

Semmel, S., Klein, R., Ones, D.S., Dilchert, S., & Wiernik, B.M. (2012). A meta-analytic review of intervention aimed at greening our workforce. Presented at the 27th Annual Conference of the Society for Industrial Organizational Psychology.

Slade, E., Dixon, L., Semmel, S. (September, 2010) Psychiatric and non-psychiatric emergency department visits in 2001 and 2006: Trends in visit duration. *Psychiatric Services*.

Limsam, M., Semmel, S. (2009). *Assessing teen risk behavior and later drug use* (Gemstone undergraduate thesis). University of Maryland, College Park, MD.

Professional and Honor Societies:

Golden Key International Honour Society
The Honor Society of Phi Kappa Phi
The Phi Beta Kappa Society
Primannum Honor Society representing Alpha Lambda Delta and Phi Eta Sigma
Psi Chi
Society for Industrial and Organizational Psychology

Activities and Leadership:

University of Minnesota

Member, Graduate Student Liaison Committee. 2010-Present.

Howard County, Maryland

Volunteer, Pets on Wheels, 2009-2010.

University of Maryland

Member, Dean's Student Advisory Council, School of Behavioral and Social Sciences, 2007-2009.

Student Representative, Department of Psychology Faculty Committee, 2007-2008.

Member, club tennis team, 2007-2008.

Director, External Public Relations, Help Center, 2007.

Community Assistant Liaison, Department of Resident Life, 2006-2007.

Graduate Course Work:

Advanced Multiple Regression Analysis, Ernest C. Davenport Jr., Ph.D.

Analysis of Psychological Data I, Rick Guyer, Ph.D.

Analysis of Psychological Data II, Christopher M. Frederico, Ph.D. and Yi Du, Ph.D.

Graduate Seminar In Psychology: Computer Adaptive Testing, David J. Weiss, Ph.D.

Graduate Seminar In Psychology: Multivariate Statistics for Social Scientists, Neils G. Waller, Ph.D.

Graduate Seminar in Psychology: Research Methods in Industrial/Organizational Psychology, Paul R. Sackett, Ph.D.

Hierarchical Linear Modeling in Educational Research, Michael R. Harwell, Ph.D.

Organizational Psychology, Aaron M. Schmidt, Ph.D.,

Personnel Psychology, Deniz S. Ones, Ph.D. and John P. Campbell, Ph.D.

Psychological Measurement: Theory and Methods, Niels G. Waller, Ph.D.

Research Laboratory in Psychology, Deniz S. Ones, Ph.D.

Seminar in Industrial and Organizational Psychology: Organizational Psychology, Aaron M. Schmidt, Ph.D. and John P. Campbell, Ph.D.

Seminar in Industrial and Organizational Psychology: Personnel Selection, Deniz S. Ones, Ph.D. and Nathan R. Kuncel, Ph.D.

Seminar in Industrial and Organizational Psychology: Workplace Interventions, John P. Campbell, Ph.D. and Nathan R. Kuncel, Ph.D.

Seminar in Psychometric Methods: Bayesian Statistics, Niels G. Waller, Ph.D.

Seminar in Psychometric Methods: Building and Testing Causal Models in the Social Sciences, Niels G. Waller, Ph.D.

Seminar in Psychometric Methods: Bayesian Analysis, Niels G. Waller, Ph.D.

Seminar in Psychometric Methods: Matrix Algebra, Niels G. Waller, Ph.D.

Seminar in Quantitative Methods: Differential Item Functioning and Measurement Invariance, Mark L. Davison, Ph.D.

Social Network Analysis: Theory and Methods, David H. Knoke, Ph.D.

Theory of Statistics, Charles J. Geyer, Ph.D.

Hobbies and Interests:

Yoga, jewelry making, home improvement projects, classic literature, writing poems, miscellaneous crafts.

Appendix D: Table of Kendall's Tau Correlations Between Rank Orders According to Selected Predictor Metrics

Article	Number of Predictors	Dependent Variable	$\tau_{\beta,r_{yx_p}}$	$\tau_{\beta,GD}$	$\tau_{\beta,\epsilon}$	$\tau_{\beta,r_S{}^2}$	$\tau_{\beta,U}$	$\tau_{\beta,C}$	$\tau_{\beta,m}$	$\tau_{r_{yx_p},GD}$
Agle et al. (2006).	3	CEO charisma	0.33	0.33	0.33	0.33	1.00	-0.33	1.00	1.00
Agle et al. (2006).	3	CEO charisma	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Agle et al. (2006).	3	CEO charisma	1.00	1.00	1.00	1.00	1.00	0.33	1.00	1.00
Agle et al. (2006).	3	CEO charisma	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Agle et al. (2006).	3	CEO charisma	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Agle et al. (2006).	3	CEO charisma	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Article	Number of Predictors	Dependent Variable	$\tau_{\beta,r_{yx_p}}$	$\tau_{\beta,GD}$	$\tau_{\beta,\epsilon}$	$\tau_{\beta,r_{S^2}}$	$\tau_{\beta,U}$	$\tau_{\beta,C}$	$\tau_{\beta,m}$	$\tau_{r_{yx_p},GD}$
Anderson et al. (2008).	12	Influence	0.55	0.70	0.76	0.55	0.88	0.45	0.76	0.85
Anderson et al. (2008).	12	Influence	0.42	0.67	0.58	0.42	0.85	0.70	0.76	0.70
Aryee et al. (2012).	5	Branch market performance	0.20	0.40	0.40	0.20	1.00	0.20	0.40	0.80
Austin (2003).	5	Goal attainment	0.60	0.60	0.80	0.60	1.00	0.60	1.00	1.00
Austin (2003).	5	Ext evaluation	1.00	1.00	1.00	1.00	0.80	0.80	1.00	1.00
Austin (2003).	5	Internal evaluation	0.40	0.40	0.40	0.40	0.80	0.40	0.80	1.00
Balkundi et al. (2011).	8	Team performance	0.79	0.79	0.79	0.79	0.79	0.79	0.93	0.71
Balkundi et al. (2011).	7	Leader charisma	0.24	0.62	0.52	0.24	0.90	0.43	0.43	0.62

Article	Number of Predictors	Dependent Variable	$\tau_{\beta,r_{yx_p}}$	$\tau_{\beta,GD}$	$\tau_{\beta,\epsilon}$	$\tau_{\beta,r_{S^2}}$	$\tau_{\beta,U}$	$\tau_{\beta,C}$	$\tau_{\beta,m}$	$\tau_{r_{yx_p},GD}$
Balkundi et al. (2011).	7	Leader centrality	0.43	0.62	0.62	0.43	0.90	0.05	0.62	0.62
Balkundi et al. (2011).	6	Leader charisma (T2)	0.33	0.47	0.47	0.33	0.73	0.20	0.73	0.87
Balkundi et al. (2011).	6	Leader centrality (T2)	0.47	0.47	0.47	0.47	0.47	-0.07	0.60	1.00
Balkundi et al. (2011).	8	Team performance (T3)	0.43	0.79	0.79	0.43	0.79	0.36	0.71	0.64
Bansal & Clelland (2004).	11	Unsystematic risk	0.71	0.67	0.64	0.71	0.85	0.38	0.78	0.75
Barnes et al.(2008).	3	Team performance	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Barnett & King (2008).	5	cumulative abnormal return	0.60	0.80	0.80	0.60	0.60	0.20	0.80	0.80

Article	Number of Predictors	Dependent Variable	$\tau_{\beta,r_{yx_p}}$	$\tau_{\beta,GD}$	$\tau_{\beta,\epsilon}$	$\tau_{\beta,r_{S^2}}$	$\tau_{\beta,U}$	$\tau_{\beta,C}$	$\tau_{\beta,m}$	$\tau_{r_{yx_p},GD}$
Barnett & King (2008).	3	cumulative abnormal return	0.33	0.33	0.33	0.33	0.33	-0.33	0.33	1.00
Barrick et al. (2010).	4	Interview score	0.67	0.67	1.00	0.67	0.67	0.67	1.00	1.00
Barrick et al. (2010).	4	Interview score (structured only; in Interview 3)	1.00	1.00	1.00	1.00	1.00	0.67	1.00	1.00
Barrick et al. (2010).	4	Second interview	0.33	0.67	1.00	0.33	1.00	-0.33	1.00	0.67
Bell et al. (2006).	5	Procedural justice expectations (1)	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Article	Number of Predictors	Dependent Variable	$\tau_{\beta,r_{yx_p}}$	$\tau_{\beta,GD}$	$\tau_{\beta,\epsilon}$	$\tau_{\beta,r_S{}^2}$	$\tau_{\beta,U}$	$\tau_{\beta,C}$	$\tau_{\beta,m}$	$\tau_{r_{yx_p},GD}$
Bell et al. (2006).	5	Distributive justice expectations (1)	0.80	0.60	0.60	0.80	0.60	-0.20	0.60	0.80
Bell et al. (2006).	5	Interpersonal justice expectations (1)	1.00	0.80	0.80	1.00	0.80	0.60	0.80	0.80
Bell et al. (2006).	5	Informational justice expectations (1)	1.00	0.40	0.40	1.00	0.40	0.40	0.40	0.40
Bell et al. (2006).	9	Test-taking efficacy (1)	0.67	0.67	0.67	0.67	0.94	0.67	0.67	1.00
Bell et al. (2006).	9	Test-taking motivation (1)	0.56	0.72	0.72	0.56	0.89	0.67	0.67	0.83
Bell et al. (2006).	9	Intention to accept job (1)	0.78	0.83	0.78	0.78	0.83	0.67	0.83	0.83

Article	Number of Predictors	Dependent Variable	$\tau_{\beta,r_{yx_p}}$	$\tau_{\beta,GD}$	$\tau_{\beta,\epsilon}$	$\tau_{\beta,r_{S^2}}$	$\tau_{\beta,U}$	$\tau_{\beta,C}$	$\tau_{\beta,m}$	$\tau_{r_{yx_p},GD}$
Bell et al. (2006).	9	Intention to recommend job (1)	0.72	0.89	0.89	0.72	0.89	0.67	0.89	0.83
Bell et al. (2006).	10	Procedural justice perceptions (2)	0.16	0.16	0.16	0.16	0.73	-0.02	0.47	0.91
Bell et al. (2006).	10	Distributive justice perceptions (2)	0.42	0.56	0.56	0.42	0.82	0.33	0.73	0.87
Bell et al. (2006).	10	Interpersonal justice perceptions (2)	0.33	0.38	0.42	0.33	0.82	0.38	0.64	0.87
Bell et al. (2006).	10	Informational justice perceptions (2)	0.64	0.73	0.73	0.64	0.91	0.56	0.73	0.91

Article	Number of Predictors	Dependent Variable	$\tau_{\beta,r_{yx_p}}$	$\tau_{\beta,GD}$	$\tau_{\beta,\epsilon}$	$\tau_{\beta,r_{S^2}}$	$\tau_{\beta,U}$	$\tau_{\beta,C}$	$\tau_{\beta,m}$	$\tau_{r_{yx_p},GD}$
Bernerth et al. (2012).	5	FICO	0.80	1.00	1.00	0.80	1.00	0.60	1.00	0.80
Bordia et al. (2008).	4	Minor offenses (Time 2)	0.33	1.00	1.00	0.33	1.00	1.00	0.33	0.33
Bordia et al. (2008).	4	Major offenses (Time 2)	0.67	1.00	0.67	0.67	1.00	0.67	0.67	0.67
Brett & Stroh (2003).	20	Work hours	0.28	0.47	0.47	0.28	0.92	0.22	0.63	0.79
Brett & Stroh (2003).	20	Work hours	0.28	0.45	0.48	0.28	0.84	0.12	0.66	0.83
Brown & Treviño (2009).	6	Self-enhancement (E)	0.60	0.87	0.73	0.60	1.00	0.07	0.60	0.73
Brown & Treviño (2009).	6	Openness to change (E)	0.47	0.60	0.60	0.47	1.00	0.07	0.60	0.87

Article	Number of Predictors	Dependent Variable	$\tau_{\beta,r_{yx_p}}$	$\tau_{\beta,GD}$	$\tau_{\beta,\epsilon}$	$\tau_{\beta,r_S{}^2}$	$\tau_{\beta,U}$	$\tau_{\beta,C}$	$\tau_{\beta,m}$	$\tau_{r_{yx_p},GD}$
Brown & Treviño (2009).	6	Conservation (E)	0.20	0.47	0.47	0.20	0.87	0.33	0.73	0.73
Brown & Treviño (2009).	5	Self-enhancement (L)	0.60	0.60	0.60	0.60	1.00	0.20	1.00	1.00
Brown & Treviño (2009).	5	Openness to change (L)	0.80	1.00	1.00	0.80	1.00	1.00	1.00	0.80
Brown & Treviño (2009).	5	Conservation (L)	0.80	0.80	0.80	0.80	1.00	1.00	0.80	1.00
Brown & Treviño (2006).	4	Organizational deviance	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Brown & Treviño (2006).	4	Values congruence	0.67	1.00	1.00	0.67	1.00	0.67	1.00	0.67
Brown & Treviño (2006).	4	Interpersonal deviance	1.00	1.00	1.00	1.00	1.00	0.67	1.00	1.00

Article	Number of Predictors	Dependent Variable	$\tau_{\beta,r_{yx_p}}$	$\tau_{\beta,GD}$	$\tau_{\beta,\epsilon}$	$\tau_{\beta,r_{S^2}}$	$\tau_{\beta,U}$	$\tau_{\beta,C}$	$\tau_{\beta,m}$	$\tau_{r_{yx_p},GD}$
Brown & Treviño (2006).	5	Organizational deviance	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Carton et al.(2014).	20	heart attack readmission prevention	0.13	0.35	0.33	0.13	0.89	0.32	0.37	0.65
Carton et al.(2014).	18	heart attack readmission prevention	0.14	0.35	0.29	0.14	0.87	0.35	0.48	0.63
Charles et al.(2013).	7	Wave 2 general affective distress	0.81	1.00	1.00	0.81	0.90	0.71	1.00	0.81
Charles et al.(2013).	6	Wave 2 general affective distress	0.87	1.00	1.00	0.87	0.87	0.73	1.00	0.87
Charles et al.(2013).	6	Wave 2 general affective distress	0.87	1.00	1.00	0.87	0.87	0.47	0.87	0.87

Article	Number of Predictors	Dependent Variable	$\tau_{\beta,r_{yx_p}}$	$\tau_{\beta,GD}$	$\tau_{\beta,\epsilon}$	$\tau_{\beta,r_{S^2}}$	$\tau_{\beta,U}$	$\tau_{\beta,C}$	$\tau_{\beta,m}$	$\tau_{r_{yx_p},GD}$
Chen et al.(2011).	4	Psychological empowerment	0.67	0.67	0.67	0.67	1.00	0.00	0.67	1.00
Chen et al.(2011).	4	Affective commitment	1.00	1.00	1.00	1.00	1.00	0.67	1.00	1.00
Chen et al.(2005).	3	Transition processes	0.33	1.00	1.00	0.33	1.00	0.33	1.00	0.33
Chen et al.(2005).	4	Action processes	0.67	0.67	0.67	0.67	0.67	0.67	0.67	1.00
Chen et al.(2005).	5	Team adaptive performance	0.40	0.80	0.80	0.40	1.00	0.00	0.80	0.60
Christmann (2004).	8	Level of internal global environmental performance standards	0.57	0.64	0.64	0.57	0.86	0.14	0.93	0.79

Article	Number of Predictors	Dependent Variable	$\tau_{\beta,r_{yx_p}}$	$\tau_{\beta,GD}$	$\tau_{\beta,\epsilon}$	$\tau_{\beta,r_{S^2}}$	$\tau_{\beta,U}$	$\tau_{\beta,C}$	$\tau_{\beta,m}$	$\tau_{r_{yx_p},GD}$
Christmann (2004).	8	Global operational environmental policy standardization	0.50	0.50	0.57	0.50	0.93	0.29	0.64	1.00
Christmann (2004).	8	Global environmental communication standardization	0.29	0.64	0.50	0.29	0.86	0.21	0.57	0.64
Conlon et al. (2006).	8	Logged Citations	0.36	0.71	0.71	0.36	0.93	0.43	0.71	0.64
Conlon et al. (2006).	10	Logged Citations	0.11	0.73	0.64	0.11	1.00	0.56	0.64	0.38
Courtright et al. (2014).	4	Engagement	1.00	1.00	1.00	1.00	1.00	0.67	1.00	1.00

Article	Number of Predictors	Dependent Variable	$\tau_{\beta,r_{yx_p}}$	$\tau_{\beta,GD}$	$\tau_{\beta,\epsilon}$	$\tau_{\beta,r_{S^2}}$	$\tau_{\beta,U}$	$\tau_{\beta,C}$	$\tau_{\beta,m}$	$\tau_{r_{yx_p},GD}$
Courtright et al. (2014).	5	Emotional exhaustion	0.80	0.80	0.80	0.80	0.80	0.80	0.80	1.00
Courtright et al. (2014).	6	Transformational leadership	0.47	0.47	0.47	0.47	0.87	0.07	0.60	1.00
Courtright et al. (2014).	6	Laissez faire leadership	0.33	0.73	0.73	0.33	0.87	0.33	0.60	0.33
Cross & Cummings (2004).	11	Performance	0.31	0.49	0.49	0.31	0.89	0.02	0.71	0.82
Cross & Cummings (2004).	11	Performance	0.42	0.56	0.56	0.42	0.82	0.35	0.64	0.85
Curhan, Elfenbein & Kilduff (2009).	11	Compensation satisfaction	0.49	0.82	0.75	0.49	0.93	0.20	0.71	0.67

Article	Number of Predictors	Dependent Variable	$\tau_{\beta,r_{yx_p}}$	$\tau_{\beta,GD}$	$\tau_{\beta,\epsilon}$	$\tau_{\beta,r_{S^2}}$	$\tau_{\beta,U}$	$\tau_{\beta,C}$	$\tau_{\beta,m}$	$\tau_{r_{yx_p},GD}$
Curhan, Elfenbein & Kilduff (2009).	11	Job satisfaction	0.45	0.75	0.67	0.45	1.00	0.31	0.85	0.71
Curhan, Elfenbein & Kilduff (2009).	11	Turnover intention	0.60	0.75	0.75	0.56	0.89	0.31	0.78	0.85
Dabos & Rousseau (2004).	3	Scientist Transactional (S)	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Dabos & Rousseau (2004).	3	Scientist Relational (S)	1.00	1.00	1.00	1.00	1.00	0.33	1.00	1.00
Dabos & Rousseau (2004).	3	Scientist Balanced (S)	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Article	Number of Predictors	Dependent Variable	$\tau_{\beta,r_{yx_p}}$	$\tau_{\beta,GD}$	$\tau_{\beta,\epsilon}$	$\tau_{\beta,r_{S^2}}$	$\tau_{\beta,U}$	$\tau_{\beta,C}$	$\tau_{\beta,m}$	$\tau_{r_{yx_p},GD}$
Dabos & Rousseau (2004).	3	Director Transactional (S)	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Dabos & Rousseau (2004).	3	Director Relational (S)	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Dabos & Rousseau (2004).	3	Director Balanced (S)	1.00	1.00	1.00	1.00	1.00	0.33	1.00	1.00
Davidson et al. (2004).	7	Discretionary current accruals	0.81	0.71	0.71	0.81	0.62	0.33	0.62	0.71
Davidson et al. (2004).	6	Discretionary current accruals	0.60	1.00	1.00	0.60	0.87	0.20	0.87	0.60
Davidson et al. (2004).	5	Discretionary current accruals	1.00	0.60	0.60	1.00	0.60	0.20	0.60	0.60

Article	Number of Predictors	Dependent Variable	$\tau_{\beta,r_{yx_p}}$	$\tau_{\beta,GD}$	$\tau_{\beta,\epsilon}$	$\tau_{\beta,r_{S^2}}$	$\tau_{\beta,U}$	$\tau_{\beta,C}$	$\tau_{\beta,m}$	$\tau_{r_{yx_p},GD}$
de Jong et al. (2014).	4	team performance	0.67	1.00	1.00	0.67	1.00	1.00	0.67	0.67
de Vries et al.(2014).	4	interteam coordination	0.67	0.67	0.67	0.67	1.00	-0.33	0.67	1.00
de Vries et al.(2014).	3	cognitive complexity	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
de Vries et al.(2014).	5	interteam coordination	0.80	0.80	0.80	0.80	1.00	0.00	0.80	1.00
DeChurch & Marks (2006).	3	Interteam coordination (explicit)	0.33	1.00	1.00	0.33	1.00	-0.33	0.33	0.33
DeChurch & Marks (2006).	3	Interteam coordination (implicit)	-1.00	0.33	0.33	-1.00	1.00	-1.00	0.33	-0.33

Article	Number of Predictors	Dependent Variable	$\tau_{\beta,r_{yx_p}}$	$\tau_{\beta,GD}$	$\tau_{\beta,\epsilon}$	$\tau_{\beta,r_{S^2}}$	$\tau_{\beta,U}$	$\tau_{\beta,C}$	$\tau_{\beta,m}$	$\tau_{r_{yx_p},GD}$
DeChurch & Marks (2006).	3	Interteam coordination (explicit)	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
DeChurch & Marks (2006).	3	Interteam coordination (implicit)	0.33	0.33	0.33	0.33	1.00	0.33	1.00	1.00
DeChurch & Marks (2006).	4	MTS performance	0.00	0.00	0.00	0.00	1.00	-0.33	0.00	1.00
DeChurch & Marks (2006).	4	MTS performance	0.67	0.67	0.67	0.67	1.00	0.33	0.67	1.00
DeChurch & Marks (2006).	4	MTS performance	0.67	1.00	0.67	0.67	1.00	0.67	1.00	0.67
DeChurch & Marks (2006).	4	MTS performance	0.67	0.67	0.67	0.67	1.00	0.33	0.67	1.00

Article	Number of Predictors	Dependent Variable	$\tau_{\boldsymbol{\beta},\boldsymbol{r_{yx_p}}}$	$\tau_{\boldsymbol{\beta},GD}$	$\tau_{\boldsymbol{\beta},\boldsymbol{\epsilon}}$	$\tau_{\boldsymbol{\beta},\boldsymbol{r_S^2}}$	$\tau_{\boldsymbol{\beta},U}$	$\tau_{\boldsymbol{\beta},C}$	$\tau_{\boldsymbol{\beta},\boldsymbol{m}}$	$\tau_{\boldsymbol{r_{yx_p}},GD}$
DeChurch & Marks (2006).	5	MTS performance	0.80	1.00	1.00	0.80	1.00	0.20	1.00	0.80
DeChurch & Marks (2006).	5	MTS performance	0.80	0.80	0.80	0.80	1.00	0.40	0.80	1.00
DeChurch et al. (2013).	5	Performance	0.80	0.80	0.80	0.80	1.00	0.60	0.80	1.00
DeChurch et al. (2013).	5	Affective outcomes	0.80	0.80	0.80	0.80	1.00	0.60	1.00	1.00
DeChurch et al. (2013).	3	Performance	0.33	0.33	0.33	0.33	1.00	0.33	0.33	1.00
DeChurch et al. (2013).	3	Affective outcomes	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
DeRue & Morgeson (2007).	3	Person–role fit (Time 5)	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Article	Number of Predictors	Dependent Variable	$\tau_{\beta,r_{yx_p}}$	$\tau_{\beta,GD}$	$\tau_{\beta,\epsilon}$	$\tau_{\beta,r_{S^2}}$	$\tau_{\beta,U}$	$\tau_{\beta,C}$	$\tau_{\beta,m}$	$\tau_{r_{yx_p},GD}$
DeRue et al. (2008).	6	team performance	0.47	0.73	0.73	0.47	1.00	0.20	0.87	0.73
Detert et al. (2008).	10	Moral disengagement	0.64	0.91	0.91	0.64	1.00	0.24	0.87	0.73
Detert et al. (2008).	11	Unethical decisions	0.45	0.75	0.75	0.45	1.00	0.45	0.75	0.71
Detert et al. (2007).	15	Operating profit	0.39	0.50	0.50	0.39	0.85	0.33	0.73	0.81
Detert et al. (2007).	15	Customer Satisfaction	0.31	0.64	0.56	0.31	0.81	0.45	0.60	0.68
Detert et al. (2007).	14	Food loss	0.69	0.80	0.76	0.69	0.87	0.45	0.74	0.85
Dierdorff & Morgeson (2007).	6	Task requirements	0.47	0.60	0.60	0.47	0.60	0.73	0.60	0.87

Article	Number of Predictors	Dependent Variable	$\tau_{\beta,r_{yx_p}}$	$\tau_{\beta,GD}$	$\tau_{\beta,\epsilon}$	$\tau_{\beta,r_{S^2}}$	$\tau_{\beta,U}$	$\tau_{\beta,C}$	$\tau_{\beta,m}$	$\tau_{r_{yx_p},GD}$
Dierdorff & Morgeson (2007).	6	Responsibility requirements	0.47	0.60	0.60	0.47	0.87	0.33	0.87	0.60
Dierdorff & Morgeson (2007).	6	Trait requirements	0.60	0.60	0.60	0.60	0.87	0.20	0.87	1.00
Drescher et al. (2014).	6	trusting behavior change	0.33	0.33	0.33	0.33	1.00	0.33	0.60	1.00
Drescher et al. (2014).	6	trusting behavior time 3	0.60	1.00	1.00	0.60	1.00	0.47	1.00	0.60
Duffy et al. (2012).	8	Social undermining, time 2	0.57	0.79	0.79	0.57	0.93	0.14	0.86	0.79

Article	Number of Predictors	Dependent Variable	$\tau_{\beta,r_{yx_p}}$	$\tau_{\beta,GD}$	$\tau_{\beta,\epsilon}$	$\tau_{\beta,r_{S^2}}$	$\tau_{\beta,U}$	$\tau_{\beta,C}$	$\tau_{\beta,m}$	$\tau_{r_{yx_p},GD}$
Eby et al. (2008).	9	Protege intentions to leave the relationship	0.33	0.44	0.44	0.33	0.78	0.00	0.67	0.89
Eby et al. (2008).	9	Protege receipt of career-related mentoring	0.39	0.56	0.50	0.39	0.83	0.33	0.83	0.83
Eby et al. (2008).	9	Protege receipt of psychosocial mentoring	0.33	0.50	0.33	0.33	0.78	0.39	0.67	0.72
Eby et al. (2008).	9	Mentor intentions to leave the relationship	0.22	0.39	0.44	0.22	0.89	0.28	0.72	0.72

Article	Number of Predictors	Dependent Variable	$\tau_{\beta,r_{yx_p}}$	$\tau_{\beta,GD}$	$\tau_{\beta,\epsilon}$	$\tau_{\beta,r_{S^2}}$	$\tau_{\beta,U}$	$\tau_{\beta,C}$	$\tau_{\beta,m}$	$\tau_{r_{yx_p},GD}$
Eby et al. (2008).	9	Mentor burnout	0.00	0.61	0.50	0.00	0.78	0.06	0.61	0.28
Edwards et al. (2006).	3	Average team performanc	0.33	0.33	0.33	0.33	1.00	-0.33	1.00	1.00
Edwards et al. (2006).	3	Average team performanc	0.33	0.33	0.33	0.33	0.33	1.00	1.00	1.00
Firth et al. (2014).	8	initial work adjustment	0.57	0.71	0.64	0.57	1.00	0.57	0.64	0.86
Firth et al. (2014).	9	work adjustment change	0.39	0.61	0.61	0.39	0.94	0.50	0.44	0.78
Firth et al. (2014).	10	premature return intention	0.38	0.69	0.64	0.38	0.78	0.51	0.78	0.69
Firth et al. (2014).	10	job satisfaction	0.38	0.69	0.69	0.38	0.96	0.69	0.78	0.69

Article	Number of Predictors	Dependent Variable	$\tau_{\beta,r_{yx_p}}$	$\tau_{\beta,GD}$	$\tau_{\beta,\epsilon}$	$\tau_{\beta,r_{S^2}}$	$\tau_{\beta,U}$	$\tau_{\beta,C}$	$\tau_{\beta,m}$	$\tau_{r_{yx_p},GD}$
Fisher (2014).	5	Coordination	0.20	0.00	0.00	0.20	0.40	0.00	0.20	0.40
Fisher (2014).	5	Interpersonal processes	0.20	0.40	0.40	0.20	1.00	0.00	1.00	0.80
Fisher (2014).	5	Coordination	0.40	0.20	0.20	0.40	0.20	0.20	0.40	0.40
Fisher (2014).	5	Interpersonal processes	0.20	0.40	0.40	0.20	0.80	-0.20	0.80	0.80
Fisher et al. (2012).	7	TMM similarity	0.62	0.71	0.81	0.62	0.71	0.71	0.81	0.71
Fisher et al. (2012).	4	Implicit coordination	0.33	1.00	1.00	0.33	1.00	1.00	0.67	0.33
Fisher et al. (2012).	4	Team performance	-0.33	-0.33	-0.33	-0.33	-0.33	1.00	0.33	1.00
Flynn & Brockner (2003).	6	Commitment	0.60	0.73	0.87	0.60	1.00	0.47	1.00	0.87

Article	Number of Predictors	Dependent Variable	$\tau_{\beta,r_{yx_p}}$	$\tau_{\beta,GD}$	$\tau_{\beta,\epsilon}$	$\tau_{\beta,r_{S^2}}$	$\tau_{\beta,U}$	$\tau_{\beta,C}$	$\tau_{\beta,m}$	$\tau_{r_{yx_p},GD}$
Flynn & Brockner (2003).	6	Commitment	0.73	0.87	0.87	0.73	0.87	0.60	1.00	0.87
Flynn & Brockner (2003).	6	Commitment	0.60	0.47	0.47	0.60	0.87	0.20	1.00	0.87
Flynn & Brockner (2003).	6	Commitment	0.47	0.60	0.60	0.47	1.00	0.33	0.87	0.87
Flynn & Schaumberg (2012).	3	Affective commitment	1.00	1.00	1.00	1.00	1.00	0.33	1.00	1.00
Flynn & Schaumberg (2012).	4	Affective commitment	1.00	1.00	1.00	1.00	0.67	0.67	1.00	1.00

Article	Number of Predictors	Dependent Variable	$\tau_{\beta,r_{yx_p}}$	$\tau_{\beta,GD}$	$\tau_{\beta,\epsilon}$	$\tau_{\beta,r_{S^2}}$	$\tau_{\beta,U}$	$\tau_{\beta,C}$	$\tau_{\beta,m}$	$\tau_{r_{yx_p},GD}$
Flynn & Schaumberg (2012).	4	Work effort	1.00	1.00	1.00	1.00	1.00	0.67	1.00	1.00
Flynn & Schaumberg (2012).	8	Affective commitment	0.43	0.79	0.86	0.43	1.00	-0.29	0.71	0.64
Flynn & Schaumberg (2012).	8	Work effort	0.57	0.57	0.57	0.57	0.86	0.29	0.57	1.00
Fritz & Sonnentag (2006).	12	health complaints t3	0.27	0.58	0.61	0.27	0.94	0.27	0.73	0.70
Fritz & Sonnentag (2006).	12	health complaints t4	0.09	0.27	0.24	0.09	0.94	0.18	0.55	0.82

Article	Number of Predictors	Dependent Variable	$\tau_{\boldsymbol{\beta}, \boldsymbol{r_{yx_p}}}$	$\tau_{\boldsymbol{\beta}, GD}$	$\tau_{\boldsymbol{\beta}, \boldsymbol{\epsilon}}$	$\tau_{\boldsymbol{\beta}, \boldsymbol{r_S^2}}$	$\tau_{\boldsymbol{\beta}, U}$	$\tau_{\boldsymbol{\beta}, C}$	$\tau_{\boldsymbol{\beta}, \boldsymbol{m}}$	$\tau_{\boldsymbol{r_{yx_p}}, GD}$
Fritz & Sonnentag (2006).	12	Exhaustion T3	0.52	0.58	0.55	0.52	0.88	0.48	0.70	0.88
Fritz & Sonnentag (2006).	12	Exhaustion T4	0.61	0.79	0.82	0.58	0.94	0.67	0.82	0.70
Fritz & Sonnentag (2006).	12	Disengagement T3	0.27	0.39	0.42	0.27	0.91	0.21	0.52	0.82
Fritz & Sonnentag (2006).	12	Disengagement T4	0.45	0.58	0.55	0.45	0.91	0.48	0.70	0.82
Fritz & Sonnentag (2006).	12	Task performance T3	0.30	0.58	0.48	0.30	1.00	0.24	0.55	0.73

Article	Number of Predictors	Dependent Variable	$\tau_{\beta,r_{yx_p}}$	$\tau_{\beta,GD}$	$\tau_{\beta,\epsilon}$	$\tau_{\beta,r_{S^2}}$	$\tau_{\beta,U}$	$\tau_{\beta,C}$	$\tau_{\beta,m}$	$\tau_{r_{yx_p},GD}$
Fritz & Sonnentag (2006).	12	Task performance T4	0.27	0.64	0.73	0.27	0.91	0.12	0.79	0.64
Fritz & Sonnentag (2006).	12	Effort expenditure T3	0.67	0.82	0.76	0.67	0.91	0.45	0.79	0.79
Fritz & Sonnentag (2006).	12	Effort expenditure T4	0.21	0.64	0.64	0.21	0.94	0.30	0.58	0.58
Fritz et al. (2010).	9	Exhaustion	0.72	0.78	0.78	0.72	1.00	0.67	0.72	0.94
Fritz et al. (2010).	9	Life satisfaction	0.56	0.72	0.72	0.56	1.00	0.56	0.67	0.83

Article	Number of Predictors	Dependent Variable	$\tau_{\beta,r_{yx_p}}$	$\tau_{\beta,GD}$	$\tau_{\beta,\epsilon}$	$\tau_{\beta,r_{S^2}}$	$\tau_{\beta,U}$	$\tau_{\beta,C}$	$\tau_{\beta,m}$	$\tau_{r_{yx_p},GD}$
Gardner et al. (2012).	9	Knowledge integration capability	0.56	0.78	0.78	0.56	0.89	0.61	0.72	0.78
Glebbeek & Bax (2004).	4	Net Result, 1995–98	0.33	1.00	1.00	0.33	1.00	0.67	0.67	0.33
Glebbeek & Bax (2004).	3	Net Result, 1995–98	1.00	1.00	1.00	1.00	1.00	0.33	1.00	1.00
Glebbeek & Bax (2004).	4	Net Result, 1997–98	1.00	1.00	1.00	1.00	1.00	0.67	1.00	1.00
Glebbeek & Bax (2004).	3	Net Result, 1997–98	1.00	1.00	1.00	1.00	1.00	-0.33	1.00	1.00
Glebbeek & Bax (2004).	5	Net Result, 1996–98	0.80	0.80	0.80	0.80	1.00	0.60	0.80	1.00
Glebbeek & Bax (2004).	4	Net Result, 1996–98	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Article	Number of Predictors	Dependent Variable	$\tau_{\beta,r_{yx_p}}$	$\tau_{\beta,GD}$	$\tau_{\beta,\epsilon}$	$\tau_{\beta,r_{S^2}}$	$\tau_{\beta,U}$	$\tau_{\beta,C}$	$\tau_{\beta,m}$	$\tau_{r_{yx_p},GD}$
Glebbeek & Bax (2004).	5	Net Result, 1997–98	1.00	1.00	1.00	1.00	0.80	0.20	1.00	1.00
Glebbeek & Bax (2004).	4	Net Result, 1997–98	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Gong et al. (2009).	14	Firm performance	0.43	0.67	0.71	0.43	0.89	0.36	0.67	0.71
Gong et al. (2009).	12	Affective commitment	0.58	0.70	0.70	0.58	0.85	0.21	0.76	0.88
Gong et al. (2009).	12	Continuance commitment	0.27	0.42	0.45	0.27	0.79	0.39	0.58	0.85
Gonzalez-Mulé et al. (2014).	5	cooperative group norms	0.60	0.80	0.80	0.60	1.00	0.40	0.80	0.80
Gonzalez-Mulé et al. (2014).	6	cwb	0.47	0.73	0.73	0.47	1.00	0.47	0.47	0.73

Article	Number of Predictors	Dependent Variable	$\tau_{\boldsymbol{\beta}, \boldsymbol{r_{yx_p}}}$	$\tau_{\boldsymbol{\beta}, GD}$	$\tau_{\boldsymbol{\beta}, \boldsymbol{\epsilon}}$	$\tau_{\boldsymbol{\beta}, \boldsymbol{r_S^2}}$	$\tau_{\boldsymbol{\beta}, U}$	$\tau_{\boldsymbol{\beta}, C}$	$\tau_{\boldsymbol{\beta}, \boldsymbol{m}}$	$\tau_{\boldsymbol{r_{yx_p}}, GD}$
Gonzalez-Mulé et al. (2014).	6	ocb	1.00	1.00	1.00	1.00	0.87	-0.20	1.00	1.00
Gonzalez-Mulé et al. (2014).	6	task performance	0.47	0.60	0.47	0.47	1.00	0.20	0.87	0.87
Gonzalez-Mulé et al. (2014).	6	job performance	1.00	0.87	0.87	1.00	1.00	0.47	1.00	0.87
Gupta et al. (2013).	6	Sales performance	1.00	1.00	1.00	1.00	0.87	0.47	1.00	1.00
Gupta et al. (2013).	6	Performance appraisal	0.87	1.00	0.73	0.87	1.00	0.33	0.87	0.87
Gupta et al. (2013).	7	Sales performance	0.81	1.00	0.90	0.81	1.00	0.24	0.90	0.81
Gupta et al. (2013).	7	Performance appraisal	0.62	0.62	0.62	0.62	0.81	0.14	0.71	0.81

Article	Number of Predictors	Dependent Variable	$\tau_{\beta,r_{yx_p}}$	$\tau_{\beta,GD}$	$\tau_{\beta,\epsilon}$	$\tau_{\beta,r_{S^2}}$	$\tau_{\beta,U}$	$\tau_{\beta,C}$	$\tau_{\beta,m}$	$\tau_{r_{yx_p},GD}$
Gupta et al. (2013).	4	Sales at Month 1	-0.33	-0.33	-0.33	-0.33	-0.33	-0.33	-0.33	1.00
Gupta et al. (2013).	4	Sales at Month 2	-0.33	0.00	0.00	-0.33	0.00	0.00	0.00	0.67
Gupta et al. (2013).	4	Sales at Month 3	0.33	0.33	0.33	0.33	1.00	0.33	0.33	1.00
Gupta et al. (2013).	4	Sales at Month 4	0.33	0.33	0.33	0.33	1.00	-0.33	0.33	1.00
Gupta et al. (2013).	4	Sales at Month 5	0.67	0.67	0.67	0.67	1.00	0.33	0.67	1.00
Gupta et al. (2013).	5	Sales at Month 1	-0.40	0.40	0.40	-0.40	0.40	0.40	0.40	0.20
Gupta et al. (2013).	5	Sales at Month 2	0.20	0.60	0.60	0.20	0.60	0.60	0.60	0.20

Article	Number of Predictors	Dependent Variable	$\tau_{\beta,r_{yxp}}$	$\tau_{\beta,GD}$	$\tau_{\beta,\epsilon}$	$\tau_{\beta,r_{S^2}}$	$\tau_{\beta,U}$	$\tau_{\beta,C}$	$\tau_{\beta,m}$	$\tau_{r_{yxp},GD}$
Gupta et al. (2013).	5	Sales at Month 3	0.00	0.00	0.00	0.00	0.40	0.00	0.20	1.00
Gupta et al. (2013).	5	Sales at Month 4	0.20	0.60	0.60	0.20	1.00	0.40	0.60	0.60
Gupta et al. (2013).	5	Sales at Month 5	0.20	0.60	0.20	0.20	1.00	-0.20	0.20	0.60
Hannah et al. (2013).	4	Adaptive decision-making	0.33	0.67	1.00	0.33	0.67	0.33	1.00	0.67
Harris et al. (2008).	8	Pay level satisfaction	0.00	0.50	0.50	0.00	0.71	0.14	0.79	0.36
Hay et al. (2011).	4	Parental reports of infance aggressiveness	1.00	1.00	1.00	1.00	0.67	1.00	1.00	1.00

Article	Number of Predictors	Dependent Variable	$\tau_{\beta,r_{yx_p}}$	$\tau_{\beta,GD}$	$\tau_{\beta,\epsilon}$	$\tau_{\beta,r_{S^2}}$	$\tau_{\beta,U}$	$\tau_{\beta,C}$	$\tau_{\beta,m}$	$\tau_{r_{yx_p},GD}$
Hay et al. (2011).	4	Observed use of instrumental force	0.33	0.67	0.67	0.33	1.00	0.33	0.33	0.67
Hay et al. (2011).	4	Observed use of bodily force	0.67	1.00	1.00	0.67	1.00	1.00	1.00	0.67
Heimeriks et al. (2012).	11	Acquisition integration performance	0.64	0.71	0.64	0.64	0.75	0.42	0.78	0.93
Heimeriks et al. (2012).	11	Risk management practices	0.27	0.64	0.56	0.27	0.82	0.45	0.64	0.64
Hewlin (2009).	4	Nonparticipative environments	0.67	0.67	0.67	0.67	1.00	-0.33	0.67	1.00

Article	Number of Predictors	Dependent Variable	$\tau_{\beta, r_{yx_p}}$	$\tau_{\beta, GD}$	$\tau_{\beta, \epsilon}$	$\tau_{\beta, r_{S^2}}$	$\tau_{\beta, U}$	$\tau_{\beta, C}$	$\tau_{\beta, m}$	$\tau_{r_{yx_p}, GD}$
Hinkin & Schriesheim (2008).	4	Supervisor effectiveness	0.00	1.00	1.00	0.00	1.00	-0.33	1.00	0.00
Hinkin & Schriesheim (2008).	4	Supervisor satisfaction	0.33	0.67	1.00	0.33	1.00	0.33	1.00	0.67
Hinkin & Schriesheim (2008).	3	Role clarity	1.00	1.00	1.00	1.00	1.00	0.33	1.00	1.00
Hirschfeld et al. (2013).	6	Within-team participation rate	0.20	0.60	0.60	0.20	1.00	-0.07	0.60	0.60
Hirschfeld et al. (2013).	10	Observed teamwork effectiveness	0.33	0.51	0.56	0.33	0.96	0.24	0.69	0.82

Article	Number of Predictors	Dependent Variable	$\tau_{\boldsymbol{\beta},\boldsymbol{r_{yx_p}}}$	$\tau_{\boldsymbol{\beta},GD}$	$\tau_{\boldsymbol{\beta},\boldsymbol{\epsilon}}$	$\tau_{\boldsymbol{\beta},\boldsymbol{r_S^2}}$	$\tau_{\boldsymbol{\beta},U}$	$\tau_{\boldsymbol{\beta},C}$	$\tau_{\boldsymbol{\beta},\boldsymbol{m}}$	$\tau_{\boldsymbol{r_{yx_p}},GD}$
Hirschfeld & Bernerth (2008).	4	Team mental efficacy	1.00	1.00	1.00	1.00	1.00	0.67	1.00	1.00
Hirschfeld & Bernerth (2008).	4	Team physical efficacy	1.00	1.00	1.00	1.00	1.00	0.00	1.00	1.00
Hirschfeld & Bernerth (2008).	8	Project X Phase 2 results	0.50	0.71	0.71	0.50	0.79	0.29	0.86	0.79
Hirschfeld & Bernerth (2008).	8	Problem solving results	0.21	0.86	0.86	0.21	1.00	0.57	0.71	0.36
Hirschfeld & Bernerth (2008).	8	Field operations results	0.50	0.79	0.64	0.50	0.86	0.14	0.93	0.71
Hirschfeld & Bernerth (2008).	9	Internal social cohesion	0.44	0.72	0.72	0.44	0.72	0.56	0.50	0.72
Hirschfeld & Bernerth (2008).	10	Observed teamwork effectiveness	0.51	0.60	0.56	0.51	0.87	0.20	0.78	0.91

Article	Number of Predictors	Dependent Variable	$\tau_{\boldsymbol{\beta}, \boldsymbol{r_{yx_p}}}$	$\tau_{\boldsymbol{\beta}, GD}$	$\tau_{\boldsymbol{\beta}, \boldsymbol{\epsilon}}$	$\tau_{\boldsymbol{\beta}, \boldsymbol{r_S^2}}$	$\tau_{\boldsymbol{\beta}, U}$	$\tau_{\boldsymbol{\beta}, C}$	$\tau_{\boldsymbol{\beta}, \boldsymbol{m}}$	$\tau_{\boldsymbol{r_{yx_p}}, GD}$
Hult et al. (2004).	3	Knowledge acquisition	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Hult et al. (2004).	4	Information distribution	0.67	0.67	0.67	0.67	0.67	0.67	1.00	1.00
Hult et al. (2004).	5	Shared meaning	0.80	0.80	0.80	0.80	0.60	0.80	0.80	1.00
Hult et al. (2004).	6	Subjective cycle time	0.60	0.73	0.60	0.60	1.00	0.07	1.00	0.87
Ilies & Judge (2003).	5	Job satisfaction	0.20	0.40	0.40	0.20	0.80	0.00	0.40	0.80
Jackson et al. (2006).	6	Citizenship behavior	0.73	0.87	0.87	0.73	1.00	0.33	0.87	0.87
Jackson et al. (2006).	6	Counter-productive behavior	0.60	0.87	0.87	0.60	0.60	0.33	0.87	0.73

Article	Number of Predictors	Dependent Variable	$\tau_{\beta,r_{yx_p}}$	$\tau_{\beta,GD}$	$\tau_{\beta,\epsilon}$	$\tau_{\beta,r_{S^2}}$	$\tau_{\beta,U}$	$\tau_{\beta,C}$	$\tau_{\beta,m}$	$\tau_{r_{yx_p},GD}$
Jackson et al. (2006).	6	Withdrawal behavior	0.60	0.87	0.87	0.60	1.00	-0.07	0.87	0.73
Jackson et al. (2006).	4	Task Performance	1.00	1.00	1.00	1.00	1.00	0.67	1.00	1.00
Janssen & Van Yperen (2004).	6	In-role job performance	0.47	0.60	0.73	0.47	0.47	0.07	1.00	0.87
Janssen & Van Yperen (2004).	6	Innovative job performance	0.47	0.60	0.60	0.47	0.73	0.07	0.87	0.87
Janssen & Van Yperen (2004).	6	Job satisfaction	0.73	0.87	0.87	0.73	1.00	0.73	0.87	0.87
Janssen & Van Yperen (2004).	5	Leader-member exchange	0.40	0.40	0.40	0.40	0.60	0.60	0.40	1.00
Jehn et al. (2010).	4	Group performance score	0.67	0.67	0.33	0.67	0.67	0.33	1.00	1.00

Article	Number of Predictors	Dependent Variable	$\tau_{\beta,r_{yx_p}}$	$\tau_{\beta,GD}$	$\tau_{\beta,\epsilon}$	$\tau_{\beta,r_{S^2}}$	$\tau_{\beta,U}$	$\tau_{\beta,C}$	$\tau_{\beta,m}$	$\tau_{r_{yx_p},GD}$
Jehn et al. (2010).	4	Creativity	0.67	0.67	0.67	0.67	1.00	-1.00	0.67	1.00
Jehn et al. (2010).	4	Group performance score	0.33	0.67	0.67	0.33	1.00	0.67	0.67	0.67
Jehn et al. (2010).	4	Creativity	0.33	0.67	0.67	0.33	1.00	0.33	0.67	0.67
Jiang et al. (2012).	3	Human Capital	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Jiang et al. (2012).	3	Employee Motivation	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Johnson, Morgeson, Ilgen, Meyer & Lloyd (2006).	6	Job satisfaction	0.87	0.87	0.87	0.87	1.00	0.73	0.87	1.00

Article	Number of Predictors	Dependent Variable	$\tau_{\beta,r_{yx_p}}$	$\tau_{\beta,GD}$	$\tau_{\beta,\epsilon}$	$\tau_{\beta,r_{S^2}}$	$\tau_{\beta,U}$	$\tau_{\beta,C}$	$\tau_{\beta,m}$	$\tau_{r_{yx_p},GD}$
Judge et al. (2007).	8	Work-related performance	0.50	0.86	0.93	0.50	1.00	0.07	0.86	0.64
Judge et al. (2007).	7	Work-related performance	0.52	0.81	0.90	0.52	1.00	-0.05	0.90	0.71
Judge et al.(2006).	6	Leadership—self	0.33	0.60	0.60	0.33	1.00	-0.33	0.87	0.73
Judge et al.(2006).	6	Leadership—other	0.20	0.60	0.73	0.20	1.00	-0.20	0.87	0.60
Judge et al.(2006).	6	Leadership—self	-0.07	0.60	0.73	-0.07	1.00	-0.33	0.73	0.33
Judge et al.(2006).	6	Leadership—other	-0.07	0.60	0.60	-0.07	1.00	0.20	0.47	0.33
Judge et al.(2006).	6	Workplace deviance—self	0.87	1.00	1.00	0.87	1.00	0.33	1.00	0.87

Article	Number of Predictors	Dependent Variable	$\tau_{\beta,r_{yx_p}}$	$\tau_{\beta,GD}$	$\tau_{\beta,\epsilon}$	$\tau_{\beta,r_{S^2}}$	$\tau_{\beta,U}$	$\tau_{\beta,C}$	$\tau_{\beta,m}$	$\tau_{r_{yx_p},GD}$
Judge et al.(2006).	6	Workplace deviance—other	0.87	1.00	1.00	0.87	1.00	0.20	1.00	0.87
Judge et al.(2006).	6	Contextual performance—self	0.60	0.60	0.60	0.60	1.00	0.47	0.87	1.00
Judge et al.(2006).	6	Contextual performance—other	0.60	0.87	0.73	0.60	1.00	0.47	0.87	0.73
Judge et al.(2006).	6	Task performance—self	0.60	0.73	0.73	0.60	1.00	0.33	0.73	0.87
Judge et al.(2006).	6	Task performance—other	0.60	0.87	0.87	0.60	1.00	0.87	0.87	0.73
Kim & Jensen (2014).	25	foreign box office performance	0.43	0.57	0.55	0.43	0.73	0.35	0.71	0.81

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Kim & Jensen (2014).	21	foreign box office performance	0.39	0.59	0.62	0.39	0.82	0.22	0.65	0.78
Kirkman et al. (2004).	3	Process improvement	1.00	1.00	1.00	1.00	1.00	0.33	1.00	1.00
Kirkman et al. (2004).	3	Team customer satisfaction	1.00	1.00	1.00	1.00	1.00	0.33	1.00	1.00
Klehe & Anderson (2007).	7	Typical Performance 1	0.71	0.71	0.71	0.71	1.00	0.52	0.81	0.81
Klehe & Anderson (2007).	9	Typical Performance 2	0.44	0.56	0.61	0.44	0.94	0.39	0.83	0.89

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Klehe & Anderson (2007).	5	Typical Performance 1	0.80	1.00	1.00	0.80	1.00	0.80	1.00	0.80
Klehe & Anderson (2007).	5	Typical Performance 2	0.60	0.80	0.80	0.60	1.00	0.20	0.80	0.80
Klehe & Anderson (2007).	3	Maximum Perforance	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Kraimer et al. (2012).	9	International Employee Identity	0.61	0.72	0.72	0.61	0.83	0.17	0.78	0.89
Kwong & Wong (2014).	5	escalation allocation	0.80	0.60	0.60	0.80	0.80	0.80	0.80	0.80

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Kwong & Wong (2014).	4	escalation allocation	0.67	0.67	0.67	0.67	1.00	0.67	1.00	1.00
Lai et al. (2009).	3	Acceptance	1.00	1.00	1.00	1.00	1.00	-0.33	1.00	1.00
Leavitt et al. (2012).	3	Sphere of concern	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Lee et al.(2014).	8	speed	0.79	0.86	0.86	0.79	1.00	0.29	1.00	0.93
Lee et al.(2014).	8	accuracy	0.57	0.79	0.79	0.57	1.00	0.36	0.79	0.79
Lee et al. (2004).	4	Performance (in-role)	0.33	1.00	1.00	0.33	1.00	0.67	0.67	0.33
Lee et al. (2004).	4	OCB (extra-role)	0.00	0.33	0.33	0.00	1.00	0.00	1.00	0.67
Lee et al. (2004).	4	Volitional absences	0.67	0.67	1.00	0.67	0.67	0.67	0.67	1.00

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Lian et al. (2012).	8	interpersonal deviance at work	0.50	0.64	0.64	0.50	0.86	0.57	0.71	0.86
Lian et al. (2012).	8	interpersonal deviance at home	0.50	0.79	0.79	0.50	0.93	0.43	0.71	0.71
Lievens & Sackett (2012).	3	Internship performance	1.00	1.00	1.00	1.00	1.00	0.33	1.00	1.00
Lievens & Sackett (2012).	3	Job performance	1.00	1.00	1.00	1.00	1.00	0.33	1.00	1.00
Lim & Ployhart (2004).	5	Transformational leadership	0.40	0.80	0.80	0.40	1.00	0.40	0.80	0.60
Madjar et al.(2011).	21	Radical Creativity	0.44	0.64	0.68	0.44	0.92	0.38	0.72	0.76

Article	Number of Predictors	Dependent Variable	$\tau_{\beta,r_{yx_p}}$	$\tau_{\beta,GD}$	$\tau_{\beta,\epsilon}$	$\tau_{\beta,r_{S^2}}$	$\tau_{\beta,U}$	$\tau_{\beta,C}$	$\tau_{\beta,m}$	$\tau_{r_{yx_p},GD}$
Madjar et al.(2011).	21	Incremental Creativity	0.32	0.49	0.49	0.32	0.87	0.47	0.57	0.69
Madjar et al.(2011).	21	Routine performance	0.16	0.41	0.39	0.16	0.86	0.13	0.57	0.71
McDonald & Westphal (2010).	11	identification with corporate elite	0.31	0.56	0.53	0.31	0.96	0.24	0.75	0.75
Moon et al. (2008).	6	Taking charge	0.60	0.87	1.00	0.60	0.73	0.20	0.87	0.73
Moon et al. (2008).	6	Taking charge (cow)	0.73	1.00	1.00	0.73	1.00	0.60	0.87	0.73
Moon et al. (2008).	6	Taking charge (sup)	0.47	0.47	0.60	0.47	1.00	0.60	0.73	1.00
Mumford et al. (2008).	7	task role performance	0.62	1.00	1.00	0.62	0.90	0.24	1.00	0.62

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Mumford et al. (2008).	7	social role performance	0.71	0.62	0.71	0.71	1.00	0.81	0.71	0.90
Mumford et al. (2008).	7	overall team performance	0.62	0.90	0.90	0.62	0.90	0.33	0.90	0.71
Mumford et al. (2008).	9	task role performance	0.44	0.83	0.83	0.44	0.94	0.28	0.83	0.61
Mumford et al. (2008).	9	social role performance	0.44	0.50	0.50	0.44	1.00	0.39	0.44	0.94
Mumford et al. (2008).	9	overall team performance	0.28	0.67	0.61	0.28	0.94	0.22	0.72	0.61
Nifadkar et al. (2012).	11	Feedback Seeking	0.13	0.20	0.24	0.13	0.89	0.02	0.53	0.85
Nifadkar et al. (2012).	11	Interaction Avoidance	0.49	0.71	0.64	0.49	0.89	0.16	0.75	0.78

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Oh & Kilduff (2008).	6	Direct brokerage	1.00	1.00	0.73	1.00	0.87	0.60	1.00	1.00
Oh & Kilduff (2008).	7	Indirect brokerage	0.52	0.62	0.62	0.52	0.81	0.33	0.90	0.90
Porath & Bateman (2006).	4	Learning goal orientation	0.67	1.00	1.00	0.67	1.00	0.00	1.00	0.67
Porath & Bateman (2006).	4	Performance-prove goal orientation	1.00	1.00	1.00	1.00	1.00	0.33	1.00	1.00
Porath & Bateman (2006).	4	Performance-avoid goal orientation	1.00	1.00	1.00	1.00	1.00	0.67	1.00	1.00

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Porath & Bateman (2006).	4	Performance	0.33	0.67	0.67	0.33	1.00	0.33	0.67	0.67
Porath & Bateman (2006).	5	Performance	-0.20	0.40	0.40	-0.20	1.00	0.20	0.20	0.40
Ragins et al. (2007).	8	degree of disclosure	0.50	0.79	0.79	0.50	1.00	0.57	0.79	0.71
Ragins et al. (2007).	8	Fear of disclosure	0.71	0.71	0.71	0.71	0.71	0.64	0.71	1.00
Raja et al. (2004).	6	Intentions to quit	0.60	0.87	0.87	0.60	0.73	0.47	1.00	0.73
Raja et al. (2004).	6	Affective commitment	0.33	0.73	0.87	0.33	1.00	0.20	0.87	0.60

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Raja et al. (2004).	6	Job satisfaction	0.33	0.33	0.33	0.33	0.87	0.20	0.73	1.00
Raja et al. (2004).	5	Intentions to quit	1.00	1.00	1.00	1.00	1.00	0.60	1.00	1.00
Raja et al. (2004).	5	Affective commitment	0.40	0.60	0.80	0.40	1.00	-0.20	1.00	0.80
Raja et al. (2004).	5	Job satisfaction	0.40	0.80	0.80	0.40	0.60	0.40	1.00	0.60
Raja et al. (2004).	6	Intentions to quit	0.47	0.47	0.47	0.47	0.73	0.33	0.87	1.00
Raja et al. (2004).	6	Affective commitment	0.33	0.47	0.60	0.33	0.87	0.33	0.60	0.87
Raja et al. (2004).	6	Job satisfaction	0.20	0.47	0.20	0.20	0.73	-0.07	0.73	0.73

Article	Number of Predictors	Dependent Variable	$\tau_{\beta,r_{yx_p}}$	$\tau_{\beta,GD}$	$\tau_{\beta,\epsilon}$	τ_{β,r_S^2}	$\tau_{\beta,U}$	$\tau_{\beta,C}$	$\tau_{\beta,m}$	$\tau_{r_{yx_p},GD}$
Raja et al. (2004).	12	Intentions to quit	0.36	0.48	0.39	0.36	0.73	0.21	0.79	0.88
Raja et al. (2004).	12	Affective commitment	0.58	0.61	0.67	0.58	0.88	0.48	0.97	0.85
Raja et al. (2004).	12	Job satisfaction	0.45	0.48	0.45	0.45	0.70	0.36	0.67	0.91
Raja et al. (2004).	10	Intentions to quit	0.20	0.24	0.24	0.20	0.96	0.07	0.64	0.87
Raja et al. (2004).	10	Affective commitment	0.64	0.60	0.64	0.64	0.78	0.56	0.96	0.96
Raja et al. (2004).	10	Job satisfaction	0.20	0.29	0.24	0.20	0.91	0.11	0.78	0.91
Raub & Liao (2012).	8	Aggregated PCSP	0.64	0.57	0.57	0.64	0.86	0.43	0.79	0.79

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Raub & Liao (2012).	10	Customer service satisfaction	0.33	0.69	0.60	0.33	0.78	0.02	0.78	0.56
Raver et al. (2010).	3	Organizational commitment	1.00	1.00	1.00	1.00	1.00	0.33	1.00	1.00
Raver et al. (2010).	3	Job satisfaction	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Raver et al. (2010).	3	Turnover intentions	0.33	1.00	1.00	0.33	1.00	-1.00	0.33	0.33
Raver et al. (2010).	3	Organizational commitment	1.00	1.00	1.00	1.00	1.00	0.33	1.00	1.00
Raver et al. (2010).	3	Job satisfaction	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Raver et al. (2010).	3	Turnover intentions	1.00	1.00	1.00	1.00	1.00	0.33	1.00	1.00

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Reynolds (2008).	7	Charitable giving	0.52	0.71	0.81	0.52	1.00	0.52	0.62	0.81
Reynolds (2008).	7	Self-reported moral behavior	0.81	0.81	0.81	0.81	1.00	0.71	0.81	1.00
Reynolds (2008).	7	Others' moral behavior	0.81	0.90	0.90	0.81	1.00	0.81	0.90	0.90
Reynolds (2008).	4	Moral awareness ("present" scenario)	1.00	1.00	1.00	1.00	0.67	0.33	1.00	1.00
Reynolds (2008).	4	Moral awareness ("absent" scenario)	0.67	1.00	1.00	0.67	1.00	0.33	1.00	0.67
Reynolds et al. (2010).	5	Considerations for shareholders	1.00	1.00	1.00	1.00	1.00	0.00	1.00	1.00

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Reynolds et al. (2010).	5	Libertarianism	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Rhee & Fiss (2014).	16	stock market reaction	0.62	0.85	0.85	0.62	0.85	0.70	0.83	0.73
Rhee & Fiss (2014).	15	stock market reaction	0.68	0.81	0.81	0.68	0.83	0.62	0.79	0.83
Rhee & Fiss (2014).	14	stock market reaction	0.76	0.78	0.78	0.76	0.80	0.56	0.76	0.93
Rhee & Fiss (2014).	14	stock market reaction	0.76	0.65	0.63	0.76	0.63	0.43	0.63	0.67
Rhee & Fiss (2014).	13	stock market reaction	0.79	0.67	0.67	0.79	0.64	0.41	0.64	0.77
Richards et al. (2011).	12	Surface acting	0.48	0.79	0.82	0.48	0.97	0.55	0.79	0.70

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Richards et al. (2011).	12	Instrumental support seeking	0.55	0.85	0.73	0.55	0.85	0.39	0.79	0.70
Richards et al. (2011).	12	Emotional support seeking	0.64	0.79	0.82	0.64	0.97	0.42	0.85	0.85
Richards et al. (2011).	12	Turnover intention	0.33	0.33	0.33	0.33	0.88	0.27	0.85	0.88
Richards et al. (2011).	12	organizational citizenship behaviors directed at the organization	0.52	0.73	0.70	0.52	0.88	0.48	0.88	0.79
Salamon & Robinson (2008).	6	Responsibility norms	0.73	0.73	0.73	0.73	1.00	0.73	0.87	1.00

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Salamon & Robinson (2008).	7	Sales	0.43	0.81	0.81	0.43	0.90	0.24	0.81	0.62
Salamon & Robinson (2008).	7	Customer service	0.24	0.52	0.62	0.24	0.81	0.24	0.71	0.52
Saparito et al. (2004).	14	Likelihood of switching	0.23	0.67	0.67	0.23	0.78	0.56	0.67	0.52
Schuelke et al. (2009).	3	Links	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Schuelke et al. (2009).	3	Coherence	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Schuelke et al. (2009).	3	Closeness	0.33	0.33	0.33	0.33	1.00	-0.33	0.33	1.00

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Schuelke et al. (2009).	3	Correlation	1.00	1.00	1.00	1.00	1.00	0.33	1.00	1.00
Schuelke et al. (2009).	5	Skill acquisition	0.80	0.80	0.80	0.80	1.00	0.80	1.00	1.00
Schuelke et al. (2009).	5	Skill transfer	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Schuelke et al. (2009).	5	Skill acquisition	0.80	0.80	0.80	0.80	0.80	0.80	1.00	1.00
Schuelke et al. (2009).	5	Skill transfer	0.80	1.00	1.00	0.80	1.00	0.80	1.00	0.80
Schuelke et al. (2009).	5	Skill acquisition	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Schuelke et al. (2009).	5	Skill transfer	0.80	0.80	0.80	0.80	1.00	0.80	0.80	1.00

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Scott & Judge (2009).	5	Organizational citizenship behavior received by employee	0.80	0.80	0.80	0.80	1.00	0.60	0.80	1.00
Scott & Judge (2009).	5	Counterproductive work behavior received by employee	0.00	0.20	0.00	0.00	0.80	0.00	0.20	0.80
Shaffer et al. (2006).	5	Cultural adjustment	0.00	0.40	0.40	0.00	0.80	-0.40	1.00	0.60
Shaffer et al. (2006).	5	Interaction adjustment	0.60	0.60	0.60	0.60	1.00	0.60	0.80	1.00
Shaffer et al. (2006).	5	Work adjustment	0.80	1.00	1.00	0.80	1.00	0.40	1.00	0.80

Article	Number of Predictors	Dependent Variable	$\tau_{\beta,r_{yx_p}}$	$\tau_{\beta,GD}$	$\tau_{\beta,\epsilon}$	$\tau_{\beta,r_{S^2}}$	$\tau_{\beta,U}$	$\tau_{\beta,C}$	$\tau_{\beta,m}$	$\tau_{r_{yx_p},GD}$
Shaffer et al. (2006).	5	Withdrawal cognitions	0.60	0.80	0.80	0.60	1.00	0.60	0.80	0.80
Shaffer et al. (2006).	5	Contextual performance	0.00	0.20	0.20	0.00	1.00	-0.20	0.20	0.80
Shaffer et al. (2006).	5	Task performance	0.80	0.60	0.40	0.80	1.00	0.60	1.00	0.80
Shaffer et al. (2006).	4	Cultural adjustment	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Shaffer et al. (2006).	4	Interaction adjustment	0.67	0.67	0.67	0.67	1.00	0.67	1.00	1.00
Shaffer et al. (2006).	4	Work adjustment	0.00	0.33	0.33	0.00	1.00	-0.33	0.67	0.67
Shaffer et al. (2006).	4	Withdrawal cognitions	0.33	1.00	1.00	0.33	1.00	0.00	1.00	0.33

Article	Number of Predictors	Dependent Variable	$\tau_{\beta,r_{yx_p}}$	$\tau_{\beta,GD}$	$\tau_{\beta,\epsilon}$	τ_{β,r_S^2}	$\tau_{\beta,U}$	$\tau_{\beta,C}$	$\tau_{\beta,m}$	$\tau_{r_{yx_p},GD}$
Shaffer et al. (2006).	4	Contextual performance	0.67	0.67	0.67	0.67	1.00	0.33	0.67	1.00
Shaffer et al. (2006).	4	Task performance	1.00	1.00	1.00	1.00	0.67	1.00	1.00	1.00
Shaffer et al. (2006).	4	Cultural adjustment	0.67	0.67	0.67	0.67	1.00	0.67	0.67	1.00
Shaffer et al. (2006).	4	Interaction adjustment	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Shaffer et al. (2006).	4	Work adjustment	1.00	1.00	1.00	1.00	1.00	0.67	1.00	1.00
Shaffer et al. (2006).	4	Withdrawal cognitions	1.00	1.00	1.00	1.00	1.00	0.67	1.00	1.00
Shaffer et al. (2006).	4	Contextual performance	1.00	1.00	1.00	1.00	1.00	0.33	1.00	1.00

Article	Number of Predictors	Dependent Variable	$\tau_{\beta,r_{yx_p}}$	$\tau_{\beta,GD}$	$\tau_{\beta,\epsilon}$	$\tau_{\beta,r_{S^2}}$	$\tau_{\beta,U}$	$\tau_{\beta,C}$	$\tau_{\beta,m}$	$\tau_{r_{yx_p},GD}$
Shaffer et al. (2006).	4	Task performance	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Shapiro et al. (2011).	19	Employee's turnover intentions	0.32	0.71	0.71	0.32	0.91	0.43	0.68	0.59
Shapiro et al. (2011).	19	Employee's psychological withdrawal	0.49	0.73	0.75	0.49	0.88	0.43	0.78	0.73
Shapiro et al. (2011).	16	Leader–member exchange	0.48	0.72	0.73	0.48	0.95	0.48	0.77	0.73
Simons et al. (2007).	7	Trust in manager	0.14	0.33	0.33	0.14	0.90	0.14	0.52	0.62
Simons et al. (2007).	7	Interpersonal justice	0.71	0.90	0.90	0.71	0.90	0.90	0.81	0.81

Article	Number of Predictors	Dependent Variable	$\tau_{\beta,r_{yx_p}}$	$\tau_{\beta,GD}$	$\tau_{\beta,\epsilon}$	$\tau_{\beta,r_{S^2}}$	$\tau_{\beta,U}$	$\tau_{\beta,C}$	$\tau_{\beta,m}$	$\tau_{r_{yx_p},GD}$
Simons et al. (2007).	7	Satisfaction	0.71	0.71	0.71	0.71	0.81	0.62	0.90	0.81
Simons et al. (2007).	7	Commitment	0.81	0.81	0.81	0.81	1.00	0.52	0.81	1.00
Simons et al. (2007).	7	Intent to stay	0.71	0.81	0.81	0.71	0.90	0.62	0.71	0.90
Slaughter et al. (2014).	14	initial belief confidence	0.30	0.49	0.47	0.30	0.82	0.25	0.63	0.80
Strauss et al. (2012).	8	Proactive career behavior	0.93	0.93	0.93	0.93	1.00	0.79	1.00	1.00
Strauss et al. (2012).	5	Proactive career behavior	0.60	0.60	0.60	0.60	1.00	0.60	0.60	1.00
Strauss et al. (2012).	6	Proactive career behavior Time 2	0.60	0.73	0.60	0.60	1.00	0.73	0.60	0.87

Article	Number of Predictors	Dependent Variable	$\tau_{\beta,r_{yx_p}}$	$\tau_{\beta,GD}$	$\tau_{\beta,\epsilon}$	$\tau_{\beta,r_{S^2}}$	$\tau_{\beta,U}$	$\tau_{\beta,C}$	$\tau_{\beta,m}$	$\tau_{r_{yx_p},GD}$
Summers et al. (2012).	5	Task performance, time 3	1.00	1.00	1.00	1.00	1.00	0.80	1.00	1.00
Takeuchi et al. (2007).	13	Collective human capital	0.31	0.64	0.64	0.31	0.85	0.67	0.69	0.62
Takeuchi et al. (2007).	13	Degree of establishment social exchange	0.28	0.49	0.56	0.28	0.67	0.26	0.56	0.79
Takeuchi et al. (2007).	13	Collective human capital	0.38	0.62	0.67	0.38	0.90	0.51	0.67	0.67
Takeuchi et al. (2007).	13	Degree of establishment social exchange	0.72	0.79	0.79	0.67	0.90	0.26	0.87	0.77

Article	Number of Predictors	Dependent Variable	$\tau_{\beta,r_{yx_p}}$	$\tau_{\beta,GD}$	$\tau_{\beta,\epsilon}$	$\tau_{\beta,r_{S^2}}$	$\tau_{\beta,U}$	$\tau_{\beta,C}$	$\tau_{\beta,m}$	$\tau_{r_{yx_p},GD}$
Takeuchi et al. (2007).	15	Relative establishment performance	0.28	0.60	0.56	0.28	0.96	0.47	0.50	0.68
Takeuchi et al. (2007).	15	Relative establishment performance	0.10	0.37	0.35	0.10	0.90	0.03	0.58	0.73
Tay et al. (2006).	11	Interview success	0.13	0.53	0.42	0.13	1.00	0.42	0.78	0.45
Tay et al. (2006).	10	Initial Interview Self Elficacy	-0.20	0.24	0.29	-0.20	0.82	0.07	0.33	0.56
Trevor & Nyberg (2008).	17	turnover	0.25	0.54	0.59	0.26	0.91	0.46	0.63	0.71
Trevor & Nyberg (2008).	16	turnover	0.22	0.53	0.50	0.23	0.92	0.37	0.58	0.68

Article	Number of Predictors	Dependent Variable	$\tau_{\beta,r_{yx_p}}$	$\tau_{\beta,GD}$	$\tau_{\beta,\epsilon}$	$\tau_{\beta,r_{S^2}}$	$\tau_{\beta,U}$	$\tau_{\beta,C}$	$\tau_{\beta,m}$	$\tau_{r_{yx_p},GD}$
Trevor & Nyberg (2008).	16	commitment	0.43	0.58	0.57	0.43	0.88	0.35	0.70	0.75
van Hooft & Noordzij (2009).	8	Job search behavior	0.36	0.50	0.50	0.36	0.79	0.36	0.57	0.86
van Hooft & Noordzij (2009).	7	Job search intention	0.90	1.00	1.00	0.90	0.90	0.81	1.00	0.90
Van Hoye & Lievens (2009).	4	Positive word-of-mouth	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Van Hoye & Lievens (2009).	4	Negative word-of-mouth	0.67	0.67	0.67	0.67	0.67	0.67	0.67	1.00
Van Hoye & Lievens (2009).	7	Organizational attractiveness	0.33	0.52	0.52	0.33	0.90	0.24	0.81	0.81
Van Iddekinge et al. (2011).	6	Technical knowledge	0.07	0.60	0.33	0.07	0.87	0.73	0.47	0.47

Article	Number of Predictors	Dependent Variable	$\tau_{\beta,r_{yx_p}}$	$\tau_{\beta,GD}$	$\tau_{\beta,\epsilon}$	$\tau_{\beta,r_{S^2}}$	$\tau_{\beta,U}$	$\tau_{\beta,C}$	$\tau_{\beta,m}$	$\tau_{r_{yx_p},GD}$
Van Iddekinge et al. (2011).	6	Interpersonal knowledge	0.20	0.87	0.60	0.20	1.00	0.60	0.60	0.33
Van Iddekinge et al. (2011).	6	Task proficiency	0.60	0.87	0.73	0.60	0.87	0.60	0.73	0.47
Van Iddekinge et al. (2011).	6	Effort	0.33	0.73	0.47	0.33	0.87	0.87	0.87	0.60
Van Iddekinge et al. (2011).	6	Continuance intentions	0.60	0.60	0.60	0.60	1.00	-0.07	0.73	1.00
Wallace et al. (2006).	4	Safety climate	1.00	1.00	1.00	1.00	1.00	0.67	1.00	1.00
Wallace et al. (2006).	5	Accidents	0.40	0.60	0.60	0.40	1.00	0.40	0.60	0.80
Wallace et al. (2006).	4	Safety climate	1.00	1.00	1.00	1.00	1.00	0.67	1.00	1.00

Article	Number of Predictors	Dependent Variable	$\tau_{\beta,r_{yx_p}}$	$\tau_{\beta,GD}$	$\tau_{\beta,\epsilon}$	$\tau_{\beta,r_{S^2}}$	$\tau_{\beta,U}$	$\tau_{\beta,C}$	$\tau_{\beta,m}$	$\tau_{r_{yx_p},GD}$
Wallace et al. (2006).	5	Accidents	0.60	0.80	0.80	0.60	0.80	0.80	0.80	0.80
Walters et al. (2010).	16	holding period returns	0.55	0.75	0.75	0.55	0.88	0.52	0.72	0.77
Walters et al. (2010).	17	holding period returns	0.51	0.76	0.74	0.51	0.81	0.51	0.72	0.75
Zhang & Peterson (2011).	7	Team performance	0.62	0.62	0.62	0.62	1.00	0.43	0.81	1.00
Zhang & Peterson (2011).	6	Advice network density	0.87	0.87	0.87	0.87	1.00	0.47	1.00	1.00

Article	Number of Predictors	Dependent Variable	$\tau_{r_{yx_p},\epsilon}$	$\tau_{r_{yx_p},r_s^2}$	$\tau_{r_{yx_p},U}$	$\tau_{r_{yx_p},C}$	$\tau_{r_{yx_p},m}$	$\tau_{GD,\epsilon}$	τ_{GD,r_s^2}
Agle et al. (2006).	3	CEO charisma	1.00	1.00	0.33	0.33	0.33	1.00	1.00
Agle et al. (2006).	3	CEO charisma	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Agle et al. (2006).	3	CEO charisma	1.00	1.00	1.00	0.33	1.00	1.00	1.00
Agle et al. (2006).	3	CEO charisma	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Agle et al. (2006).	3	CEO charisma	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Agle et al. (2006).	3	CEO charisma	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Anderson et al. (2008).	12	Influence	0.79	1.00	0.48	0.85	0.79	0.94	0.85

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Anderson et al. (2008).	12	Influence	0.85	1.00	0.45	0.30	0.67	0.85	0.70
Aryee et al. (2012).	5	Branch market performance	0.80	1.00	0.20	0.20	0.80	1.00	0.80
Austin (2003).	5	Goal attainment	0.80	1.00	0.60	1.00	0.60	0.80	1.00
Austin (2003).	5	Ext evaluation	1.00	1.00	0.80	0.80	1.00	1.00	1.00
Austin (2003).	5	Internal evaluation	1.00	1.00	0.20	1.00	0.60	1.00	1.00
Balkundi et al. (2011).	8	Team performance	0.71	1.00	0.71	0.57	0.86	1.00	0.71
Balkundi et al. (2011).	7	Leader charisma	0.71	1.00	0.33	0.43	0.81	0.90	0.62
Balkundi et al. (2011).	7	Leader centrality	0.62	1.00	0.52	0.43	0.81	1.00	0.62

Article	Number of Predictors	Dependent Variable	$\tau_{r_{yxp},\epsilon}$	τ_{r_{yxp},r_s^2}	$\tau_{r_{yxp},U}$	$\tau_{r_{yxp},C}$	$\tau_{r_{yxp},m}$	$\tau_{GD,\epsilon}$	τ_{GD,r_s^2}
Balkundi et al. (2011).	6	Leader charisma (T2)	0.87	1.00	0.33	0.07	0.60	1.00	0.87
Balkundi et al. (2011).	6	Leader centrality (T2)	1.00	1.00	0.20	0.47	0.87	1.00	1.00
Balkundi et al. (2011).	8	Team performance (T3)	0.64	1.00	0.36	0.36	0.71	1.00	0.64
Bansal & Clelland (2004).	11	Unsystematic risk	0.71	1.00	0.71	0.67	0.93	0.96	0.75
Barnes et al.(2008).	3	Team performance	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Barnett & King (2008).	5	cumulative abnormal return	0.80	1.00	1.00	0.60	0.80	1.00	0.80
Barnett & King (2008).	3	cumulative abnormal return	1.00	1.00	1.00	0.33	1.00	1.00	1.00

Article	Number of Predictors	Dependent Variable	$\tau_{r_{yx_p},\epsilon}$	$\tau_{r_{yx_p},r_s^2}$	$\tau_{r_{yx_p},U}$	$\tau_{r_{yx_p},C}$	$\tau_{r_{yx_p},m}$	$\tau_{GD,\epsilon}$	τ_{GD,r_s^2}
Barrick et al. (2010).	4	Interview score	0.67	1.00	0.33	1.00	0.67	0.67	1.00
Barrick et al. (2010).	4	Interview score (structured only; in Interview 3)	1.00	1.00	1.00	0.67	1.00	1.00	1.00
Barrick et al. (2010).	4	Second interview	0.33	1.00	0.33	0.33	0.33	0.67	0.67
Bell et al. (2006).	5	Procedural justice expectations (1)	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Bell et al. (2006).	5	Distributive justice expectations (1)	0.80	1.00	0.80	0.00	0.80	1.00	0.80

Article	Number of Predictors	Dependent Variable	$\tau_{\boldsymbol{r_{yx_p}},\boldsymbol{\epsilon}}$	$\tau_{\boldsymbol{r_{yx_p}},\boldsymbol{r_s^2}}$	$\tau_{\boldsymbol{r_{yx_p}},U}$	$\tau_{\boldsymbol{r_{yx_p}},C}$	$\tau_{\boldsymbol{r_{yx_p}},\boldsymbol{m}}$	$\tau_{GD,\boldsymbol{\epsilon}}$	$\tau_{GD,\boldsymbol{r_s^2}}$
Bell et al. (2006).	5	Interpersonal justice expectations (1)	0.80	1.00	0.80	0.60	0.80	1.00	0.80
Bell et al. (2006).	5	Informational justice expectations (1)	0.40	1.00	0.40	0.40	0.40	1.00	0.40
Bell et al. (2006).	9	Test-taking efficacy (1)	1.00	1.00	0.72	0.89	1.00	1.00	1.00
Bell et al. (2006).	9	Test-taking motivation (1)	0.83	1.00	0.67	0.67	0.89	1.00	0.83
Bell et al. (2006).	9	Intention to accept job (1)	0.78	1.00	0.61	0.89	0.83	0.94	0.83
Bell et al. (2006).	9	Intention to recommend job (1)	0.83	1.00	0.83	0.94	0.83	1.00	0.83

Article	Number of Predictors	Dependent Variable	$\tau_{r_{yx_p},\epsilon}$	$\tau_{r_{yx_p},r_s^2}$	$\tau_{r_{yx_p},U}$	$\tau_{r_{yx_p},C}$	$\tau_{r_{yx_p},m}$	$\tau_{GD,\epsilon}$	τ_{GD,r_s^2}
Bell et al. (2006).	10	Procedural justice perceptions (2)	0.91	1.00	0.24	0.56	0.69	1.00	0.91
Bell et al. (2006).	10	Distributive justice perceptions (2)	0.87	1.00	0.42	0.64	0.69	1.00	0.87
Bell et al. (2006).	10	Interpersonal justice perceptions (2)	0.82	1.00	0.42	0.78	0.69	0.96	0.87
Bell et al. (2006).	10	Informational justice perceptions (2)	0.82	1.00	0.56	0.73	0.91	0.91	0.91
Bernerth et al. (2012).	5	FICO	0.80	1.00	0.80	0.80	0.80	1.00	0.80

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Bordia et al. (2008).	4	Minor offenses (Time 2)	0.33	1.00	0.33	0.33	1.00	1.00	0.33
Bordia et al. (2008).	4	Major offenses (Time 2)	1.00	1.00	0.67	1.00	1.00	0.67	0.67
Brett & Stroh (2003).	20	Work hours	0.73	1.00	0.35	0.62	0.65	0.92	0.79
Brett & Stroh (2003).	20	Work hours	0.78	1.00	0.36	0.81	0.62	0.95	0.83
Brown & Treviño (2009).	6	Self-enhancement (E)	0.87	1.00	0.60	-0.33	1.00	0.87	0.73
Brown & Treviño (2009).	6	Openness to change (E)	0.87	1.00	0.47	0.07	0.87	1.00	0.87
Brown & Treviño (2009).	6	Conservation (E)	0.73	1.00	0.33	0.60	0.47	1.00	0.73

Article	Number of Predictors	Dependent Variable	$\tau_{r_{yxp},\epsilon}$	τ_{r_{yxp},r_s^2}	$\tau_{r_{yxp},U}$	$\tau_{r_{yxp},C}$	$\tau_{r_{yxp},m}$	$\tau_{GD,\epsilon}$	τ_{GD,r_s^2}
Brown & Treviño (2009).	5	Self-enhancement (L)	1.00	1.00	0.60	0.60	0.60	1.00	1.00
Brown & Treviño (2009).	5	Openness to change (L)	0.80	1.00	0.80	0.80	0.80	1.00	0.80
Brown & Treviño (2009).	5	Conservation (L)	1.00	1.00	0.80	0.80	1.00	1.00	1.00
Brown & Treviño (2006).	4	Organizational deviance	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Brown & Treviño (2006).	4	Values congruence	0.67	1.00	0.67	1.00	0.67	1.00	0.67
Brown & Treviño (2006).	4	Interpersonal deviance	1.00	1.00	1.00	0.67	1.00	1.00	1.00
Brown & Treviño (2006).	5	Organizational deviance	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Article	Number of Predictors	Dependent Variable	$\tau_{r_{yx_p},\epsilon}$	$\tau_{r_{yx_p},r_s^2}$	$\tau_{r_{yx_p},U}$	$\tau_{r_{yx_p},C}$	$\tau_{r_{yx_p},m}$	$\tau_{GD,\epsilon}$	τ_{GD,r_s^2}
Carton et al.(2014).	20	heart attack readmission prevention	0.63	0.98	0.11	0.47	0.76	0.96	0.67
Carton et al.(2014).	18	heart attack readmission prevention	0.63	0.97	0.08	0.48	0.66	0.90	0.66
Charles et al.(2013).	7	Wave 2 general affective distress	0.81	1.00	0.71	0.90	0.81	1.00	0.81
Charles et al.(2013).	6	Wave 2 general affective distress	0.87	1.00	0.73	0.87	0.87	1.00	0.87
Charles et al.(2013).	6	Wave 2 general affective distress	0.87	1.00	0.73	0.60	0.73	1.00	0.87
Chen et al.(2011).	4	Psychological empowerment	1.00	1.00	0.67	-0.33	1.00	1.00	1.00

Article	Number of Predictors	Dependent Variable	$\tau_{r_{yx_p},\epsilon}$	$\tau_{r_{yx_p},r_s^2}$	$\tau_{r_{yx_p},U}$	$\tau_{r_{yx_p},C}$	$\tau_{r_{yx_p},m}$	$\tau_{GD,\epsilon}$	τ_{GD,r_s^2}
Chen et al.(2011).	4	Affective commitment	1.00	1.00	1.00	0.67	1.00	1.00	1.00
Chen et al.(2005).	3	Transition processes	0.33	1.00	0.33	1.00	0.33	1.00	0.33
Chen et al.(2005).	4	Action processes	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Chen et al.(2005).	5	Team adaptive performance	0.60	1.00	0.40	0.60	0.60	1.00	0.60
Christmann (2004).	8	Level of internal global environmental performance standards	0.79	1.00	0.57	0.57	0.64	1.00	0.79

Article	Number of Predictors	Dependent Variable	$\tau_{r_{yx_p},\epsilon}$	$\tau_{r_{yx_p},r_s^2}$	$\tau_{r_{yx_p},U}$	$\tau_{r_{yx_p},C}$	$\tau_{r_{yx_p},m}$	$\tau_{GD,\epsilon}$	τ_{GD,r_s^2}
Christmann (2004).	8	Global operational environmental policy standardization	0.93	1.00	0.57	0.79	0.86	0.93	1.00
Christmann (2004).	8	Global environmental communication standardization	0.79	1.00	0.43	0.21	0.71	0.86	0.64
Conlon et al. (2006).	8	Logged Citations	0.64	1.00	0.43	0.07	0.64	1.00	0.64
Conlon et al. (2006).	10	Logged Citations	0.38	1.00	0.11	0.02	0.47	0.91	0.38
Courtright et al. (2014).	4	Engagement	1.00	1.00	1.00	0.67	1.00	1.00	1.00

Article	Number of Predictors	Dependent Variable	$\tau_{r_{yx_p},\epsilon}$	$\tau_{r_{yx_p},r_s^2}$	$\tau_{r_{yx_p},U}$	$\tau_{r_{yx_p},C}$	$\tau_{r_{yx_p},m}$	$\tau_{GD,\epsilon}$	τ_{GD,r_s^2}
Courtright et al. (2014).	5	Emotional exhaustion	1.00	1.00	0.60	1.00	1.00	1.00	1.00
Courtright et al. (2014).	6	Transformational leadership	1.00	1.00	0.60	0.33	0.87	1.00	1.00
Courtright et al. (2014).	6	Laissez faire leadership	0.33	1.00	0.20	-0.33	0.73	1.00	0.33
Cross & Cummings (2004).	11	Performance	0.82	1.00	0.35	0.56	0.60	1.00	0.82
Cross & Cummings (2004).	11	Performance	0.85	1.00	0.45	0.78	0.78	1.00	0.85
Curhan, Elfenbein & Kilduff (2009).	11	Compensation satisfaction	0.75	1.00	0.49	0.42	0.78	0.93	0.67

Article	Number of Predictors	Dependent Variable	$\tau_{r_{yx_p},\epsilon}$	$\tau_{r_{yx_p},r_s^2}$	$\tau_{r_{yx_p},U}$	$\tau_{r_{yx_p},C}$	$\tau_{r_{yx_p},m}$	$\tau_{GD,\epsilon}$	τ_{GD,r_s^2}
Curhan, Elfenbein & Kilduff (2009).	11	Job satisfaction	0.78	1.00	0.45	0.13	0.60	0.93	0.71
Curhan, Elfenbein & Kilduff (2009).	11	Turnover intention	0.85	0.96	0.56	0.49	0.75	1.00	0.82
Dabos & Rousseau (2004).	3	Scientist Transactional (S)	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Dabos & Rousseau (2004).	3	Scientist Relational (S)	1.00	1.00	1.00	0.33	1.00	1.00	1.00
Dabos & Rousseau (2004).	3	Scientist Balanced (S)	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Article	Number of Predictors	Dependent Variable	$\tau_{r_{yx_p},\epsilon}$	$\tau_{r_{yx_p},r_s^2}$	$\tau_{r_{yx_p},U}$	$\tau_{r_{yx_p},C}$	$\tau_{r_{yx_p},m}$	$\tau_{GD,\epsilon}$	τ_{GD,r_s^2}
Dabos & Rousseau (2004).	3	Director Transactional (S)	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Dabos & Rousseau (2004).	3	Director Relational (S)	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Dabos & Rousseau (2004).	3	Director Balanced (S)	1.00	1.00	1.00	0.33	1.00	1.00	1.00
Davidson et al. (2004).	7	Discretionary current accruals	0.71	1.00	0.62	0.33	0.62	1.00	0.71
Davidson et al. (2004).	6	Discretionary current accruals	0.60	1.00	0.47	0.07	0.47	1.00	0.60
Davidson et al. (2004).	5	Discretionary current accruals	0.60	1.00	0.60	0.20	0.60	1.00	0.60

Article	Number of Predictors	Dependent Variable	$\tau_{r_{yxp},\epsilon}$	τ_{r_{yxp},r_s^2}	$\tau_{r_{yxp},U}$	$\tau_{r_{yxp},C}$	$\tau_{r_{yxp},m}$	$\tau_{GD,\epsilon}$	τ_{GD,r_s^2}
de Jong et al. (2014).	4	team performance	0.67	1.00	0.67	0.67	1.00	1.00	0.67
de Vries et al.(2014).	4	interteam coordination	1.00	1.00	0.67	0.00	1.00	1.00	1.00
de Vries et al.(2014).	3	cognitive complexity	1.00	1.00	1.00	1.00	1.00	1.00	1.00
de Vries et al.(2014).	5	interteam coordination	1.00	1.00	0.80	0.20	1.00	1.00	1.00
DeChurch & Marks (2006).	3	Interteam coordination (explicit)	0.33	1.00	0.33	0.33	1.00	1.00	0.33
DeChurch & Marks (2006).	3	Interteam coordination (implicit)	-0.33	1.00	-1.00	1.00	-0.33	1.00	-0.33

Article	Number of Predictors	Dependent Variable	$\tau_{r_{yxp},\epsilon}$	τ_{r_{yxp},r_s^2}	$\tau_{r_{yxp},U}$	$\tau_{r_{yxp},C}$	$\tau_{r_{yxp},m}$	$\tau_{GD,\epsilon}$	τ_{GD,r_s^2}
DeChurch & Marks (2006).	3	Interteam coordination (explicit)	1.00	1.00	1.00	1.00	1.00	1.00	1.00
DeChurch & Marks (2006).	3	Interteam coordination (implicit)	1.00	1.00	0.33	1.00	0.33	1.00	1.00
DeChurch & Marks (2006).	4	MTS performance	1.00	1.00	0.00	0.67	1.00	1.00	1.00
DeChurch & Marks (2006).	4	MTS performance	1.00	1.00	0.67	0.67	1.00	1.00	1.00
DeChurch & Marks (2006).	4	MTS performance	1.00	1.00	0.67	1.00	0.67	0.67	0.67
DeChurch & Marks (2006).	4	MTS performance	1.00	1.00	0.67	0.67	1.00	1.00	1.00

Article	Number of Predictors	Dependent Variable	$\tau_{r_{yx_p},\epsilon}$	$\tau_{r_{yx_p},r_s^2}$	$\tau_{r_{yx_p},U}$	$\tau_{r_{yx_p},C}$	$\tau_{r_{yx_p},m}$	$\tau_{GD,\epsilon}$	τ_{GD,r_s^2}
DeChurch & Marks (2006).	5	MTS performance	0.80	1.00	0.80	0.40	0.80	1.00	0.80
DeChurch & Marks (2006).	5	MTS performance	1.00	1.00	0.80	0.60	1.00	1.00	1.00
DeChurch et al. (2013).	5	Performance	1.00	1.00	0.80	0.80	1.00	1.00	1.00
DeChurch et al. (2013).	5	Affective outcomes	1.00	1.00	0.80	0.80	0.80	1.00	1.00
DeChurch et al. (2013).	3	Performance	1.00	1.00	0.33	1.00	1.00	1.00	1.00
DeChurch et al. (2013).	3	Affective outcomes	1.00	1.00	1.00	1.00	1.00	1.00	1.00
DeRue & Morgeson (2007).	3	Person–role fit (Time 5)	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Article	Number of Predictors	Dependent Variable	$\tau_{r_{yx_p},\epsilon}$	$\tau_{r_{yx_p},r_s^2}$	$\tau_{r_{yx_p},U}$	$\tau_{r_{yx_p},C}$	$\tau_{r_{yx_p},m}$	$\tau_{GD,\epsilon}$	τ_{GD,r_s^2}
DeRue et al. (2008).	6	team performance	0.73	1.00	0.47	0.20	0.60	1.00	0.73
Detert et al. (2008).	10	Moral disengagement	0.73	1.00	0.64	0.33	0.78	1.00	0.73
Detert et al. (2008).	11	Unethical decisions	0.71	1.00	0.45	0.78	0.71	1.00	0.71
Detert et al. (2007).	15	Operating profit	0.81	1.00	0.35	0.94	0.66	1.00	0.81
Detert et al. (2007).	15	Customer Satisfaction	0.75	1.00	0.43	0.64	0.71	0.92	0.68
Detert et al. (2007).	14	Food loss	0.80	1.00	0.60	0.63	0.91	0.91	0.85
Dierdorff & Morgeson (2007).	6	Task requirements	0.87	1.00	0.60	0.20	0.87	1.00	0.87

Article	Number of Predictors	Dependent Variable	$\tau_{r_{yx_p},\epsilon}$	$\tau_{r_{yx_p},r_s^2}$	$\tau_{r_{yx_p},U}$	$\tau_{r_{yx_p},C}$	$\tau_{r_{yx_p},m}$	$\tau_{GD,\epsilon}$	τ_{GD,r_s^2}
Dierdorff & Morgeson (2007).	6	Responsibility requirements	0.60	1.00	0.33	0.87	0.60	1.00	0.60
Dierdorff & Morgeson (2007).	6	Trait requirements	1.00	1.00	0.47	0.60	0.73	1.00	1.00
Drescher et al. (2014).	6	trusting behavior change	1.00	1.00	0.33	1.00	0.73	1.00	1.00
Drescher et al. (2014).	6	trusting behavior time 3	0.60	1.00	0.60	0.87	0.60	1.00	0.60
Duffy et al. (2012).	8	Social undermining, time 2	0.79	1.00	0.64	0.14	0.71	1.00	0.79

Article	Number of Predictors	Dependent Variable	$\tau_{r_{yx_p},\epsilon}$	$\tau_{r_{yx_p},r_s^2}$	$\tau_{r_{yx_p},U}$	$\tau_{r_{yx_p},C}$	$\tau_{r_{yx_p},m}$	$\tau_{GD,\epsilon}$	τ_{GD,r_s^2}
Eby et al. (2008).	9	Protege intentions to leave the relationship	0.89	1.00	0.33	0.67	0.67	1.00	0.89
Eby et al. (2008).	9	Protege receipt of career-related mentoring	0.78	1.00	0.33	0.94	0.56	0.94	0.83
Eby et al. (2008).	9	Protege receipt of psychosocial mentoring	0.89	1.00	0.22	0.94	0.67	0.83	0.72
Eby et al. (2008).	9	Mentor intentions to leave the relationship	0.67	1.00	0.11	0.94	0.50	0.94	0.72

Article	Number of Predictors	Dependent Variable	$\tau_{r_{yx_p},\epsilon}$	$\tau_{r_{yx_p},r_s^2}$	$\tau_{r_{yx_p},U}$	$\tau_{r_{yx_p},C}$	$\tau_{r_{yx_p},m}$	$\tau_{GD,\epsilon}$	τ_{GD,r_s^2}
Eby et al. (2008).	9	Mentor burnout	0.28	1.00	0.00	0.39	0.39	0.89	0.28
Edwards et al. (2006).	3	Average team performanc	1.00	1.00	0.33	0.33	0.33	1.00	1.00
Edwards et al. (2006).	3	Average team performanc	1.00	1.00	1.00	0.33	0.33	1.00	1.00
Firth et al. (2014).	8	initial work adjustment	0.93	1.00	0.57	0.86	0.93	0.93	0.86
Firth et al. (2014).	9	work adjustment change	0.78	1.00	0.44	0.56	0.94	1.00	0.78
Firth et al. (2014).	10	premature return intention	0.73	1.00	0.33	0.24	0.60	0.96	0.69
Firth et al. (2014).	10	job satisfaction	0.69	1.00	0.42	0.69	0.60	0.91	0.69

Article	Number of Predictors	Dependent Variable	$\tau_{r_{yx_p},\epsilon}$	$\tau_{r_{yx_p},r_s^2}$	$\tau_{r_{yx_p},U}$	$\tau_{r_{yx_p},C}$	$\tau_{r_{yx_p},m}$	$\tau_{GD,\epsilon}$	τ_{GD,r_s^2}
Fisher (2014).	5	Coordination	0.40	1.00	0.00	0.40	1.00	1.00	0.40
Fisher (2014).	5	Interpersonal processes	0.80	1.00	0.20	0.80	0.20	1.00	0.80
Fisher (2014).	5	Coordination	0.40	1.00	0.40	0.40	1.00	1.00	0.40
Fisher (2014).	5	Interpersonal processes	0.80	1.00	0.40	0.60	0.40	1.00	0.80
Fisher et al. (2012).	7	TMM similarity	0.62	1.00	0.71	0.52	0.81	0.90	0.71
Fisher et al. (2012).	4	Implicit coordination	0.33	1.00	0.33	0.33	0.67	1.00	0.33
Fisher et al. (2012).	4	Team performance	1.00	1.00	1.00	-0.33	0.33	1.00	1.00
Flynn & Brockner (2003).	6	Commitment	0.73	1.00	0.60	0.87	0.60	0.87	0.87

Article	Number of Predictors	Dependent Variable	$\tau_{r_{yx_p},\epsilon}$	$\tau_{r_{yx_p},r_s^2}$	$\tau_{r_{yx_p},U}$	$\tau_{r_{yx_p},C}$	$\tau_{r_{yx_p},m}$	$\tau_{GD,\epsilon}$	τ_{GD,r_s^2}
Flynn & Brockner (2003).	6	Commitment	0.87	1.00	0.60	0.87	0.73	1.00	0.87
Flynn & Brockner (2003).	6	Commitment	0.87	1.00	0.47	0.60	0.60	1.00	0.87
Flynn & Brockner (2003).	6	Commitment	0.87	1.00	0.47	0.87	0.60	1.00	0.87
Flynn & Schaumberg (2012).	3	Affective commitment	1.00	1.00	1.00	0.33	1.00	1.00	1.00
Flynn & Schaumberg (2012).	4	Affective commitment	1.00	1.00	0.67	0.67	1.00	1.00	1.00

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Flynn & Schaumberg (2012).	4	Work effort	1.00	1.00	1.00	0.67	1.00	1.00	1.00
Flynn & Schaumberg (2012).	8	Affective commitment	0.57	1.00	0.43	0.00	0.71	0.93	0.64
Flynn & Schaumberg (2012).	8	Work effort	1.00	1.00	0.57	0.57	1.00	1.00	1.00
Fritz & Sonnentag (2006).	12	health complaints t3	0.67	1.00	0.27	0.82	0.55	0.97	0.70
Fritz & Sonnentag (2006).	12	health complaints t4	0.79	1.00	0.09	0.85	0.55	0.91	0.82

Article	Number of Predictors	Dependent Variable	$\tau_{r_{yxp},\epsilon}$	τ_{r_{yxp},r_s^2}	$\tau_{r_{yxp},U}$	$\tau_{r_{yxp},C}$	$\tau_{r_{yxp},m}$	$\tau_{GD,\epsilon}$	τ_{GD,r_s^2}
Fritz & Sonnentag (2006).	12	Exhaustion T3	0.85	1.00	0.45	0.91	0.82	0.91	0.88
Fritz & Sonnentag (2006).	12	Exhaustion T4	0.67	0.97	0.61	0.82	0.79	0.97	0.73
Fritz & Sonnentag (2006).	12	Disengagement T3	0.85	1.00	0.30	0.94	0.76	0.97	0.82
Fritz & Sonnentag (2006).	12	Disengagement T4	0.79	1.00	0.36	0.85	0.76	0.97	0.82
Fritz & Sonnentag (2006).	12	Task performance T3	0.82	1.00	0.30	0.21	0.76	0.91	0.73

Article	Number of Predictors	Dependent Variable	$\tau_{r_{yx_p},\epsilon}$	$\tau_{r_{yx_p},r_s^2}$	$\tau_{r_{yx_p},U}$	$\tau_{r_{yx_p},C}$	$\tau_{r_{yx_p},m}$	$\tau_{GD,\epsilon}$	τ_{GD,r_s^2}
Fritz & Sonnentag (2006).	12	Task performance T4	0.55	1.00	0.30	0.85	0.48	0.91	0.64
Fritz & Sonnentag (2006).	12	Effort expenditure T3	0.73	1.00	0.64	0.55	0.88	0.94	0.79
Fritz & Sonnentag (2006).	12	Effort expenditure T4	0.58	1.00	0.21	0.42	0.64	1.00	0.58
Fritz et al. (2010).	9	Exhaustion	0.94	1.00	0.72	0.72	1.00	1.00	0.94
Fritz et al. (2010).	9	Life satisfaction	0.83	1.00	0.56	0.89	0.89	1.00	0.83

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Gardner et al. (2012).	9	Knowledge integration capability	0.78	1.00	0.67	0.72	0.83	1.00	0.78
Glebbeek & Bax (2004).	4	Net Result, 1995–98	0.33	1.00	0.33	0.00	0.67	1.00	0.33
Glebbeek & Bax (2004).	3	Net Result, 1995–98	1.00	1.00	1.00	0.33	1.00	1.00	1.00
Glebbeek & Bax (2004).	4	Net Result, 1997–98	1.00	1.00	1.00	0.67	1.00	1.00	1.00
Glebbeek & Bax (2004).	3	Net Result, 1997–98	1.00	1.00	1.00	-0.33	1.00	1.00	1.00
Glebbeek & Bax (2004).	5	Net Result, 1996–98	1.00	1.00	0.80	0.40	1.00	1.00	1.00
Glebbeek & Bax (2004).	4	Net Result, 1996–98	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Article	Number of Predictors	Dependent Variable	$\tau_{r_{yx_p},\epsilon}$	$\tau_{r_{yx_p},r_s^2}$	$\tau_{r_{yx_p},U}$	$\tau_{r_{yx_p},C}$	$\tau_{r_{yx_p},m}$	$\tau_{GD,\epsilon}$	τ_{GD,r_s^2}
Glebbeek & Bax (2004).	5	Net Result, 1997–98	1.00	1.00	0.80	0.20	1.00	1.00	1.00
Glebbeek & Bax (2004).	4	Net Result, 1997–98	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Gong et al. (2009).	14	Firm performance	0.71	1.00	0.32	0.49	0.76	0.91	0.71
Gong et al. (2009).	12	Affective commitment	0.88	1.00	0.67	0.64	0.82	1.00	0.88
Gong et al. (2009).	12	Continuance commitment	0.82	1.00	0.30	0.64	0.70	0.91	0.85
Gonzalez-Mulé et al. (2014).	5	cooperative group norms	0.80	1.00	0.60	0.80	0.80	1.00	0.80
Gonzalez-Mulé et al. (2014).	6	cwb	0.73	1.00	0.47	-0.07	1.00	1.00	0.73

Article	Number of Predictors	Dependent Variable	$\tau_{r_{yx_p},\epsilon}$	$\tau_{r_{yx_p},r_s^2}$	$\tau_{r_{yx_p},U}$	$\tau_{r_{yx_p},C}$	$\tau_{r_{yx_p},m}$	$\tau_{GD,\epsilon}$	τ_{GD,r_s^2}
Gonzalez-Mulé et al. (2014).	6	ocb	1.00	1.00	0.87	-0.20	1.00	1.00	1.00
Gonzalez-Mulé et al. (2014).	6	task performance	1.00	1.00	0.47	0.47	0.60	0.87	0.87
Gonzalez-Mulé et al. (2014).	6	job performance	0.87	1.00	1.00	0.47	1.00	1.00	0.87
Gupta et al. (2013).	6	Sales performance	1.00	1.00	0.87	0.47	1.00	1.00	1.00
Gupta et al. (2013).	6	Performance appraisal	0.87	1.00	0.87	0.20	1.00	0.73	0.87
Gupta et al. (2013).	7	Sales performance	0.71	1.00	0.81	0.43	0.90	0.90	0.81
Gupta et al. (2013).	7	Performance appraisal	0.81	1.00	0.43	0.52	0.90	0.81	0.81

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Gupta et al. (2013).	4	Sales at Month 1	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Gupta et al. (2013).	4	Sales at Month 2	0.67	1.00	0.67	0.67	0.67	1.00	0.67
Gupta et al. (2013).	4	Sales at Month 3	1.00	1.00	0.33	-0.33	1.00	1.00	1.00
Gupta et al. (2013).	4	Sales at Month 4	1.00	1.00	0.33	-0.33	1.00	1.00	1.00
Gupta et al. (2013).	4	Sales at Month 5	1.00	1.00	0.67	0.67	1.00	1.00	1.00
Gupta et al. (2013).	5	Sales at Month 1	0.20	1.00	0.20	0.20	0.20	1.00	0.20
Gupta et al. (2013).	5	Sales at Month 2	0.20	1.00	0.20	0.20	0.20	1.00	0.20

Article	Number of Predictors	Dependent Variable	$\tau_{r_{yxp},\epsilon}$	τ_{r_{yxp},r_s^2}	$\tau_{r_{yxp},U}$	$\tau_{r_{yxp},C}$	$\tau_{r_{yxp},m}$	$\tau_{GD,\epsilon}$	τ_{GD,r_s^2}
Gupta et al. (2013).	5	Sales at Month 3	1.00	1.00	0.60	0.20	0.80	1.00	1.00
Gupta et al. (2013).	5	Sales at Month 4	0.60	1.00	0.20	0.00	0.60	1.00	0.60
Gupta et al. (2013).	5	Sales at Month 5	1.00	1.00	0.20	0.60	1.00	0.60	0.60
Hannah et al. (2013).	4	Adaptive decision-making	0.33	1.00	0.00	1.00	0.33	0.67	0.67
Harris et al. (2008).	8	Pay level satisfaction	0.36	1.00	0.29	-0.43	0.21	1.00	0.36
Hay et al. (2011).	4	Parental reports of infance aggressiveness	1.00	1.00	0.67	1.00	1.00	1.00	1.00

Article	Number of Predictors	Dependent Variable	$\tau_{r_{yx_p},\epsilon}$	$\tau_{r_{yx_p},r_s^2}$	$\tau_{r_{yx_p},U}$	$\tau_{r_{yx_p},C}$	$\tau_{r_{yx_p},m}$	$\tau_{GD,\epsilon}$	τ_{GD,r_s^2}
Hay et al. (2011).	4	Observed use of instrumental force	0.67	1.00	0.33	0.33	1.00	1.00	0.67
Hay et al. (2011).	4	Observed use of bodily force	0.67	1.00	0.67	0.67	0.67	1.00	0.67
Heimeriks et al. (2012).	11	Acquisition integration performance	0.85	1.00	0.53	0.78	0.85	0.93	0.93
Heimeriks et al. (2012).	11	Risk management practices	0.71	1.00	0.24	0.82	0.64	0.93	0.64
Hewlin (2009).	4	Nonparticipative environments	1.00	1.00	0.67	0.00	1.00	1.00	1.00

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Hinkin & Schriesheim (2008).	4	Supervisor effectiveness	0.00	1.00	0.00	0.67	0.00	1.00	0.00
Hinkin & Schriesheim (2008).	4	Supervisor satisfaction	0.33	1.00	0.33	1.00	0.33	0.67	0.67
Hinkin & Schriesheim (2008).	3	Role clarity	1.00	1.00	1.00	0.33	1.00	1.00	1.00
Hirschfeld et al. (2013).	6	Within-team participation rate	0.60	1.00	0.20	0.47	0.60	1.00	0.60
Hirschfeld et al. (2013).	10	Observed teamwork effectiveness	0.78	1.00	0.29	0.91	0.64	0.87	0.82

Article	Number of Predictors	Dependent Variable	$\tau_{r_{yx_p},\epsilon}$	$\tau_{r_{yx_p},r_s^2}$	$\tau_{r_{yx_p},U}$	$\tau_{r_{yx_p},C}$	$\tau_{r_{yx_p},m}$	$\tau_{GD,\epsilon}$	τ_{GD,r_s^2}
Hirschfeld & Bernerth (2008).	4	Team mental efficacy	1.00	1.00	1.00	0.67	1.00	1.00	1.00
Hirschfeld & Bernerth (2008).	4	Team physical efficacy	1.00	1.00	1.00	0.00	1.00	1.00	1.00
Hirschfeld & Bernerth (2008).	8	Project X Phase 2 results	0.79	1.00	0.29	0.79	0.64	1.00	0.79
Hirschfeld & Bernerth (2008).	8	Problem solving results	0.36	1.00	0.21	0.21	0.50	1.00	0.36
Hirschfeld & Bernerth (2008).	8	Field operations results	0.71	1.00	0.50	0.21	0.57	0.86	0.71
Hirschfeld & Bernerth (2008).	9	Internal social cohesion	0.72	1.00	0.17	0.67	0.94	1.00	0.72
Hirschfeld & Bernerth (2008).	10	Observed teamwork effectiveness	0.87	1.00	0.47	0.69	0.73	0.96	0.91

Article	Number of Predictors	Dependent Variable	$\tau_{r_{yx_p},\epsilon}$	$\tau_{r_{yx_p},r_s^2}$	$\tau_{r_{yx_p},U}$	$\tau_{r_{yx_p},C}$	$\tau_{r_{yx_p},m}$	$\tau_{GD,\epsilon}$	τ_{GD,r_s^2}
Hult et al. (2004).	3	Knowledge acquisition	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Hult et al. (2004).	4	Information distribution	1.00	1.00	0.33	1.00	0.67	1.00	1.00
Hult et al. (2004).	5	Shared meaning	1.00	1.00	0.40	1.00	1.00	1.00	1.00
Hult et al. (2004).	6	Subjective cycle time	1.00	1.00	0.60	0.47	0.60	0.87	0.87
Ilies & Judge (2003).	5	Job satisfaction	0.80	1.00	0.40	0.80	0.80	1.00	0.80
Jackson et al. (2006).	6	Citizenship behavior	0.87	1.00	0.73	0.07	0.87	1.00	0.87
Jackson et al. (2006).	6	Counter-productive behavior	0.73	1.00	0.47	0.47	0.73	1.00	0.73

Article	Number of Predictors	Dependent Variable	$\tau_{r_{yx_p},\epsilon}$	$\tau_{r_{yx_p},r_s^2}$	$\tau_{r_{yx_p},U}$	$\tau_{r_{yx_p},C}$	$\tau_{r_{yx_p},m}$	$\tau_{GD,\epsilon}$	τ_{GD,r_s^2}
Jackson et al. (2006).	6	Withdrawal behavior	0.73	1.00	0.60	-0.20	0.73	1.00	0.73
Jackson et al. (2006).	4	Task Performance	1.00	1.00	1.00	0.67	1.00	1.00	1.00
Janssen & Van Yperen (2004).	6	In-role job performance	0.73	1.00	0.47	0.33	0.47	0.87	0.87
Janssen & Van Yperen (2004).	6	Innovative job performance	0.87	1.00	0.73	0.60	0.60	1.00	0.87
Janssen & Van Yperen (2004).	6	Job satisfaction	0.87	1.00	0.73	1.00	0.87	1.00	0.87
Janssen & Van Yperen (2004).	5	Leader-member exchange	1.00	1.00	0.80	0.40	1.00	1.00	1.00
Jehn et al. (2010).	4	Group performance score	0.67	1.00	1.00	0.67	0.67	0.67	1.00

Article	Number of Predictors	Dependent Variable	$\tau_{r_{yx_p},\epsilon}$	$\tau_{r_{yx_p},r_s^2}$	$\tau_{r_{yx_p},U}$	$\tau_{r_{yx_p},C}$	$\tau_{r_{yx_p},m}$	$\tau_{GD,\epsilon}$	τ_{GD,r_s^2}
Jehn et al. (2010).	4	Creativity	1.00	1.00	0.67	-0.67	1.00	1.00	1.00
Jehn et al. (2010).	4	Group performance score	0.67	1.00	0.33	0.00	0.67	1.00	0.67
Jehn et al. (2010).	4	Creativity	0.67	1.00	0.33	0.33	0.67	1.00	0.67
Jiang et al. (2012).	3	Human Capital	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Jiang et al. (2012).	3	Employee Motivation	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Johnson, Morgeson, Ilgen, Meyer & Lloyd (2006).	6	Job satisfaction	1.00	1.00	0.87	0.87	1.00	1.00	1.00

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Judge et al. (2007).	8	Work-related performance	0.57	1.00	0.50	0.57	0.64	0.93	0.64
Judge et al. (2007).	7	Work-related performance	0.62	1.00	0.52	0.24	0.62	0.90	0.71
Judge et al.(2006).	6	Leadership—self	0.73	1.00	0.33	0.33	0.47	1.00	0.73
Judge et al.(2006).	6	Leadership—other	0.47	1.00	0.20	0.33	0.33	0.87	0.60
Judge et al.(2006).	6	Leadership—self	0.20	1.00	-0.07	0.73	0.20	0.87	0.33
Judge et al.(2006).	6	Leadership—other	0.33	1.00	-0.07	0.20	0.47	1.00	0.33
Judge et al.(2006).	6	Workplace deviance—self	0.87	1.00	0.87	0.47	0.87	1.00	0.87

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Judge et al.(2006).	6	Workplace deviance—other	0.87	1.00	0.87	0.07	0.87	1.00	0.87
Judge et al.(2006).	6	Contextual performance—self	1.00	1.00	0.60	0.87	0.73	1.00	1.00
Judge et al.(2006).	6	Contextual performance—other	0.60	1.00	0.60	0.60	0.73	0.87	0.73
Judge et al.(2006).	6	Task performance—self	0.87	1.00	0.60	0.73	0.87	1.00	0.87
Judge et al.(2006).	6	Task performance—other	0.73	1.00	0.60	0.47	0.73	1.00	0.73
Kim & Jensen (2014).	25	foreign box office performance	0.81	1.00	0.45	0.89	0.71	0.96	0.81

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Kim & Jensen (2014).	21	foreign box office performance	0.73	1.00	0.44	0.77	0.74	0.95	0.78
Kirkman et al. (2004).	3	Process improvement	1.00	1.00	1.00	0.33	1.00	1.00	1.00
Kirkman et al. (2004).	3	Team customer satisfaction	1.00	1.00	1.00	0.33	1.00	1.00	1.00
Klehe & Anderson (2007).	7	Typical Performance 1	0.81	1.00	0.71	0.81	0.90	1.00	0.81
Klehe & Anderson (2007).	9	Typical Performance 2	0.83	1.00	0.39	0.94	0.61	0.94	0.89

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Klehe & Anderson (2007).	5	Typical Performance 1	0.80	1.00	0.80	1.00	0.80	1.00	0.80
Klehe & Anderson (2007).	5	Typical Performance 2	0.80	1.00	0.60	0.60	0.80	1.00	0.80
Klehe & Anderson (2007).	3	Maximum Perforance	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Kraimer et al. (2012).	9	International Employee Identity	0.89	1.00	0.56	0.44	0.83	1.00	0.89
Kwong & Wong (2014).	5	escalation allocation	0.80	1.00	0.60	1.00	1.00	1.00	0.80

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Kwong & Wong (2014).	4	escalation allocation	1.00	1.00	0.67	1.00	0.67	1.00	1.00
Lai et al. (2009).	3	Acceptance	1.00	1.00	1.00	-0.33	1.00	1.00	1.00
Leavitt et al. (2012).	3	Sphere of concern	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Lee et al.(2014).	8	speed	0.93	1.00	0.79	0.36	0.79	1.00	0.93
Lee et al.(2014).	8	accuracy	0.79	1.00	0.57	0.50	0.79	1.00	0.79
Lee et al. (2004).	4	Performance (in-role)	0.33	1.00	0.33	0.00	0.67	1.00	0.33
Lee et al. (2004).	4	OCB (extra-role)	0.67	1.00	0.00	0.33	0.00	1.00	0.67
Lee et al. (2004).	4	Volitional absences	0.67	1.00	1.00	1.00	1.00	0.67	1.00

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Lian et al. (2012).	8	interpersonal deviance at work	0.86	1.00	0.36	0.93	0.79	1.00	0.86
Lian et al. (2012).	8	interpersonal deviance at home	0.71	1.00	0.57	0.93	0.79	0.86	0.71
Lievens & Sackett (2012).	3	Internship performance	1.00	1.00	1.00	0.33	1.00	1.00	1.00
Lievens & Sackett (2012).	3	Job performance	1.00	1.00	1.00	0.33	1.00	1.00	1.00
Lim & Ployhart (2004).	5	Transformational leadership	0.60	1.00	0.40	1.00	0.60	1.00	0.60
Madjar et al.(2011).	21	Radical Creativity	0.74	1.00	0.48	0.68	0.71	0.96	0.76

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Madjar et al.(2011).	21	Incremental Creativity	0.67	1.00	0.42	0.59	0.73	0.96	0.69
Madjar et al.(2011).	21	Routine performance	0.68	1.00	0.27	0.59	0.59	0.92	0.71
McDonald & Westphal (2010).	11	identification with corporate elite	0.78	1.00	0.35	0.42	0.56	0.96	0.75
Moon et al. (2008).	6	Taking charge	0.60	1.00	0.33	0.07	0.73	0.87	0.73
Moon et al. (2008).	6	Taking charge (cow)	0.73	1.00	0.73	0.60	0.87	1.00	0.73
Moon et al. (2008).	6	Taking charge (sup)	0.87	1.00	0.47	0.87	0.73	0.87	1.00
Mumford et al. (2008).	7	task role performance	0.62	1.00	0.52	0.05	0.62	1.00	0.62

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Mumford et al. (2008).	7	social role performance	1.00	1.00	0.71	0.71	1.00	0.90	0.90
Mumford et al. (2008).	7	overall team performance	0.71	1.00	0.71	0.14	0.71	1.00	0.71
Mumford et al. (2008).	9	task role performance	0.61	1.00	0.39	0.50	0.61	1.00	0.61
Mumford et al. (2008).	9	social role performance	0.94	1.00	0.44	0.72	1.00	1.00	0.94
Mumford et al. (2008).	9	overall team performance	0.67	1.00	0.22	0.50	0.56	0.94	0.61
Nifadkar et al. (2012).	11	Feedback Seeking	0.82	1.00	0.09	0.82	0.60	0.96	0.85
Nifadkar et al. (2012).	11	Interaction Avoidance	0.78	1.00	0.45	0.45	0.75	0.93	0.78

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Oh & Kilduff (2008).	6	Direct brokerage	0.73	1.00	0.87	0.60	1.00	0.73	1.00
Oh & Kilduff (2008).	7	Indirect brokerage	0.90	1.00	0.71	0.81	0.62	1.00	0.90
Porath & Bateman (2006).	4	Learning goal orientation	0.67	1.00	0.67	0.33	0.67	1.00	0.67
Porath & Bateman (2006).	4	Performance-prove goal orientation	1.00	1.00	1.00	0.33	1.00	1.00	1.00
Porath & Bateman (2006).	4	Performance-avoid goal orientation	1.00	1.00	1.00	0.67	1.00	1.00	1.00

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Porath & Bateman (2006).	4	Performance	0.67	1.00	0.33	-0.33	0.67	1.00	0.67
Porath & Bateman (2006).	5	Performance	0.40	1.00	-0.20	0.20	0.60	1.00	0.40
Ragins et al. (2007).	8	degree of disclosure	0.71	1.00	0.50	0.79	0.71	1.00	0.71
Ragins et al. (2007).	8	Fear of disclosure	1.00	1.00	0.86	0.93	1.00	1.00	1.00
Raja et al. (2004).	6	Intentions to quit	0.73	1.00	0.33	0.87	0.60	1.00	0.73
Raja et al. (2004).	6	Affective commitment	0.47	1.00	0.33	0.87	0.47	0.87	0.60

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Raja et al. (2004).	6	Job satisfaction	1.00	1.00	0.20	0.87	0.60	1.00	1.00
Raja et al. (2004).	5	Intentions to quit	1.00	1.00	1.00	0.60	1.00	1.00	1.00
Raja et al. (2004).	5	Affective commitment	0.60	1.00	0.40	0.40	0.40	0.80	0.80
Raja et al. (2004).	5	Job satisfaction	0.60	1.00	0.00	1.00	0.40	1.00	0.60
Raja et al. (2004).	6	Intentions to quit	1.00	1.00	0.20	0.87	0.60	1.00	1.00
Raja et al. (2004).	6	Affective commitment	0.73	1.00	0.47	1.00	0.73	0.87	0.87
Raja et al. (2004).	6	Job satisfaction	1.00	1.00	0.20	0.73	0.47	0.73	0.73

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Raja et al. (2004).	12	Intentions to quit	0.85	1.00	0.15	0.85	0.58	0.91	0.88
Raja et al. (2004).	12	Affective commitment	0.85	1.00	0.52	0.91	0.61	0.94	0.85
Raja et al. (2004).	12	Job satisfaction	0.94	1.00	0.27	0.91	0.79	0.97	0.91
Raja et al. (2004).	10	Intentions to quit	0.87	1.00	0.16	0.87	0.56	1.00	0.87
Raja et al. (2004).	10	Affective commitment	0.91	1.00	0.69	0.91	0.69	0.96	0.96
Raja et al. (2004).	10	Job satisfaction	0.96	1.00	0.20	0.91	0.42	0.96	0.91
Raub & Liao (2012).	8	Aggregated PCSP	0.79	1.00	0.50	0.36	0.86	1.00	0.79

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Raub & Liao (2012).	10	Customer service satisfaction	0.38	1.00	0.29	0.33	0.56	0.82	0.56
Raver et al. (2010).	3	Organizational commitment	1.00	1.00	1.00	0.33	1.00	1.00	1.00
Raver et al. (2010).	3	Job satisfaction	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Raver et al. (2010).	3	Turnover intentions	0.33	1.00	0.33	-0.33	1.00	1.00	0.33
Raver et al. (2010).	3	Organizational commitment	1.00	1.00	1.00	0.33	1.00	1.00	1.00
Raver et al. (2010).	3	Job satisfaction	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Raver et al. (2010).	3	Turnover intentions	1.00	1.00	1.00	0.33	1.00	1.00	1.00

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Reynolds (2008).	7	Charitable giving	0.71	1.00	0.52	0.62	0.90	0.90	0.81
Reynolds (2008).	7	Self-reported moral behavior	1.00	1.00	0.81	0.90	1.00	1.00	1.00
Reynolds (2008).	7	Others' moral behavior	0.90	1.00	0.81	0.81	0.90	1.00	0.90
Reynolds (2008).	4	Moral awareness ("present" scenario)	1.00	1.00	0.67	0.33	1.00	1.00	1.00
Reynolds (2008).	4	Moral awareness ("absent" scenario)	0.67	1.00	0.67	0.67	0.67	1.00	0.67
Reynolds et al. (2010).	5	Considerations for shareholders	1.00	1.00	1.00	0.00	1.00	1.00	1.00

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Reynolds et al. (2010).	5	Libertarianism	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Rhee & Fiss (2014).	16	stock market reaction	0.73	1.00	0.73	0.55	0.75	1.00	0.73
Rhee & Fiss (2014).	15	stock market reaction	0.83	1.00	0.77	0.64	0.85	1.00	0.83
Rhee & Fiss (2014).	14	stock market reaction	0.93	1.00	0.87	0.71	0.96	1.00	0.93
Rhee & Fiss (2014).	14	stock market reaction	0.69	1.00	0.65	0.45	0.69	0.98	0.67
Rhee & Fiss (2014).	13	stock market reaction	0.77	1.00	0.74	0.51	0.79	1.00	0.77
Richards et al. (2011).	12	Surface acting	0.67	1.00	0.52	0.52	0.70	0.97	0.70

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Richards et al. (2011).	12	Instrumental support seeking	0.70	1.00	0.58	0.85	0.76	0.88	0.70
Richards et al. (2011).	12	Emotional support seeking	0.82	1.00	0.67	0.79	0.79	0.97	0.85
Richards et al. (2011).	12	Turnover intention	0.94	1.00	0.21	0.94	0.48	0.94	0.88
Richards et al. (2011).	12	organizational citizenship behaviors directed at the organization	0.76	1.00	0.52	0.97	0.64	0.97	0.79
Salamon & Robinson (2008).	6	Responsibility norms	1.00	1.00	0.73	1.00	0.87	1.00	1.00

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Salamon & Robinson (2008).	7	Sales	0.62	1.00	0.33	0.24	0.62	1.00	0.62
Salamon & Robinson (2008).	7	Customer service	0.43	1.00	0.05	0.81	0.52	0.90	0.52
Saparito et al. (2004).	14	Likelihood of switching	0.52	1.00	0.27	0.45	0.47	1.00	0.52
Schuelke et al. (2009).	3	Links	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Schuelke et al. (2009).	3	Coherence	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Schuelke et al. (2009).	3	Closeness	1.00	1.00	0.33	0.33	1.00	1.00	1.00

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Schuelke et al. (2009).	3	Correlation	1.00	1.00	1.00	0.33	1.00	1.00	1.00
Schuelke et al. (2009).	5	Skill acquisition	1.00	1.00	0.80	1.00	0.80	1.00	1.00
Schuelke et al. (2009).	5	Skill transfer	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Schuelke et al. (2009).	5	Skill acquisition	1.00	1.00	1.00	1.00	0.80	1.00	1.00
Schuelke et al. (2009).	5	Skill transfer	0.80	1.00	0.80	1.00	0.80	1.00	0.80
Schuelke et al. (2009).	5	Skill acquisition	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Schuelke et al. (2009).	5	Skill transfer	1.00	1.00	0.80	1.00	1.00	1.00	1.00

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Scott & Judge (2009).	5	Organizational citizenship behavior received by employee	1.00	1.00	0.80	0.80	1.00	1.00	1.00
Scott & Judge (2009).	5	Counterproductive work behavior received by employee	1.00	1.00	0.20	1.00	0.80	0.80	0.80
Shaffer et al. (2006).	5	Cultural adjustment	0.60	1.00	0.20	0.60	0.00	1.00	0.60
Shaffer et al. (2006).	5	Interaction adjustment	1.00	1.00	0.60	1.00	0.80	1.00	1.00
Shaffer et al. (2006).	5	Work adjustment	0.80	1.00	0.80	0.60	0.80	1.00	0.80

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Shaffer et al. (2006).	5	Withdrawal cognitions	0.80	1.00	0.60	0.60	0.80	1.00	0.80
Shaffer et al. (2006).	5	Contextual performance	0.80	1.00	0.00	0.80	0.80	1.00	0.80
Shaffer et al. (2006).	5	Task performance	0.60	1.00	0.80	0.80	0.80	0.80	0.80
Shaffer et al. (2006).	4	Cultural adjustment	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Shaffer et al. (2006).	4	Interaction adjustment	1.00	1.00	0.67	1.00	0.67	1.00	1.00
Shaffer et al. (2006).	4	Work adjustment	0.67	1.00	0.00	0.67	0.33	1.00	0.67
Shaffer et al. (2006).	4	Withdrawal cognitions	0.33	1.00	0.33	0.67	0.33	1.00	0.33

Article	Number of Predictors	Dependent Variable	$\tau_{r_{yx_p},\epsilon}$	$\tau_{r_{yx_p},r_s^2}$	$\tau_{r_{yx_p},U}$	$\tau_{r_{yx_p},C}$	$\tau_{r_{yx_p},m}$	$\tau_{GD,\epsilon}$	τ_{GD,r_s^2}
Shaffer et al. (2006).	4	Contextual performance	1.00	1.00	0.67	0.67	1.00	1.00	1.00
Shaffer et al. (2006).	4	Task performance	1.00	1.00	0.67	1.00	1.00	1.00	1.00
Shaffer et al. (2006).	4	Cultural adjustment	1.00	1.00	0.67	1.00	1.00	1.00	1.00
Shaffer et al. (2006).	4	Interaction adjustment	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Shaffer et al. (2006).	4	Work adjustment	1.00	1.00	1.00	0.67	1.00	1.00	1.00
Shaffer et al. (2006).	4	Withdrawal cognitions	1.00	1.00	1.00	0.67	1.00	1.00	1.00
Shaffer et al. (2006).	4	Contextual performance	1.00	1.00	1.00	0.33	1.00	1.00	1.00

Article	Number of Predictors	Dependent Variable	$\tau_{r_{yx_p},\epsilon}$	$\tau_{r_{yx_p},r_s^2}$	$\tau_{r_{yx_p},U}$	$\tau_{r_{yx_p},C}$	$\tau_{r_{yx_p},m}$	$\tau_{GD,\epsilon}$	τ_{GD,r_s^2}
Shaffer et al. (2006).	4	Task performance	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Shapiro et al. (2011).	19	Employee's turnover intentions	0.61	1.00	0.32	0.29	0.64	0.98	0.59
Shapiro et al. (2011).	19	Employee's psychological withdrawal	0.68	1.00	0.49	0.75	0.68	0.95	0.73
Shapiro et al. (2011).	16	Leader–member exchange	0.72	1.00	0.47	0.60	0.72	0.98	0.73
Simons et al. (2007).	7	Trust in manager	0.62	1.00	0.24	1.00	0.62	1.00	0.62
Simons et al. (2007).	7	Interpersonal justice	0.81	1.00	0.62	0.81	0.71	1.00	0.81

Article	Number of Predictors	Dependent Variable	$\tau_{r_{yx_p},\epsilon}$	$\tau_{r_{yx_p},r_s^2}$	$\tau_{r_{yx_p},U}$	$\tau_{r_{yx_p},C}$	$\tau_{r_{yx_p},m}$	$\tau_{GD,\epsilon}$	τ_{GD,r_s^2}
Simons et al. (2007).	7	Satisfaction	0.81	1.00	0.52	0.90	0.81	1.00	0.81
Simons et al. (2007).	7	Commitment	1.00	1.00	0.81	0.71	1.00	1.00	1.00
Simons et al. (2007).	7	Intent to stay	0.90	1.00	0.81	0.52	1.00	1.00	0.90
Slaughter et al. (2014).	14	initial belief confidence	0.82	1.00	0.43	0.91	0.67	0.93	0.80
Strauss et al. (2012).	8	Proactive career behavior	1.00	1.00	0.93	0.86	0.93	1.00	1.00
Strauss et al. (2012).	5	Proactive career behavior	1.00	1.00	0.60	1.00	1.00	1.00	1.00
Strauss et al. (2012).	6	Proactive career behavior Time 2	1.00	1.00	0.60	0.87	1.00	0.87	0.87

Article	Number of Predictors	Dependent Variable	$\tau_{r_{yx_p},\epsilon}$	$\tau_{r_{yx_p},r_s^2}$	$\tau_{r_{yx_p},U}$	$\tau_{r_{yx_p},C}$	$\tau_{r_{yx_p},m}$	$\tau_{GD,\epsilon}$	τ_{GD,r_s^2}
Summers et al. (2012).	5	Task performance, time 3	1.00	1.00	1.00	0.80	1.00	1.00	1.00
Takeuchi et al. (2007).	13	Collective human capital	0.62	1.00	0.36	0.33	0.62	0.95	0.62
Takeuchi et al. (2007).	13	Degree of establishment social exchange	0.72	0.95	0.36	0.82	0.72	0.92	0.79
Takeuchi et al. (2007).	13	Collective human capital	0.56	1.00	0.38	0.26	0.72	0.90	0.67
Takeuchi et al. (2007).	13	Degree of establishment social exchange	0.82	0.95	0.67	0.28	0.79	0.95	0.77

Article	Number of Predictors	Dependent Variable	$\tau_{r_{yx_p},\epsilon}$	$\tau_{r_{yx_p},r_s^2}$	$\tau_{r_{yx_p},U}$	$\tau_{r_{yx_p},C}$	$\tau_{r_{yx_p},m}$	$\tau_{GD,\epsilon}$	τ_{GD,r_s^2}
Takeuchi et al. (2007).	15	Relative establishment performance	0.71	1.00	0.24	0.39	0.77	0.96	0.68
Takeuchi et al. (2007).	15	Relative establishment performance	0.75	1.00	0.09	0.16	0.52	0.98	0.73
Tay et al. (2006).	11	Interview success	0.56	1.00	0.13	0.20	0.35	0.89	0.45
Tay et al. (2006).	10	Initial Interview Self Elficacy	0.51	1.00	-0.02	0.11	0.47	0.96	0.56
Trevor & Nyberg (2008).	17	turnover	0.66	0.99	0.28	0.74	0.62	0.93	0.72
Trevor & Nyberg (2008).	16	turnover	0.72	0.98	0.30	0.78	0.63	0.97	0.70

Article	Number of Predictors	Dependent Variable	$\tau_{r_{yx_p},\epsilon}$	$\tau_{r_{yx_p},r_s^2}$	$\tau_{r_{yx_p},U}$	$\tau_{r_{yx_p},C}$	$\tau_{r_{yx_p},m}$	$\tau_{GD,\epsilon}$	τ_{GD,r_s^2}
Trevor & Nyberg (2008).	16	commitment	0.77	1.00	0.42	0.58	0.73	0.98	0.75
van Hooft & Noordzij (2009).	8	Job search behavior	0.86	1.00	0.14	0.71	0.79	1.00	0.86
van Hooft & Noordzij (2009).	7	Job search intention	0.90	1.00	0.81	0.90	0.90	1.00	0.90
Van Hoye & Lievens (2009).	4	Positive word-of-mouth	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Van Hoye & Lievens (2009).	4	Negative word-of-mouth	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Van Hoye & Lievens (2009).	7	Organizational attractiveness	0.81	1.00	0.43	0.90	0.52	1.00	0.81
Van Iddekinge et al. (2011).	6	Technical knowledge	0.73	1.00	0.20	0.07	0.60	0.73	0.47

Article	Number of Predictors	Dependent Variable	$\tau_{r_{yxp},\epsilon}$	τ_{r_{yxp},r_s^2}	$\tau_{r_{yxp},U}$	$\tau_{r_{yxp},C}$	$\tau_{r_{yxp},m}$	$\tau_{GD,\epsilon}$	τ_{GD,r_s^2}
Van Iddekinge et al. (2011).	6	Interpersonal knowledge	0.60	1.00	0.20	0.60	0.60	0.73	0.33
Van Iddekinge et al. (2011).	6	Task proficiency	0.60	1.00	0.47	0.20	0.87	0.87	0.47
Van Iddekinge et al. (2011).	6	Effort	0.87	1.00	0.47	0.47	0.47	0.73	0.60
Van Iddekinge et al. (2011).	6	Continuance intentions	1.00	1.00	0.60	0.33	0.87	1.00	1.00
Wallace et al. (2006).	4	Safety climate	1.00	1.00	1.00	0.67	1.00	1.00	1.00
Wallace et al. (2006).	5	Accidents	0.80	1.00	0.40	1.00	0.80	1.00	0.80
Wallace et al. (2006).	4	Safety climate	1.00	1.00	1.00	0.67	1.00	1.00	1.00

Article	Number of Predictors	Dependent Variable	$\tau_{r_{yx_p},\epsilon}$	$\tau_{r_{yx_p},r_s^2}$	$\tau_{r_{yx_p},U}$	$\tau_{r_{yx_p},C}$	$\tau_{r_{yx_p},m}$	$\tau_{GD,\epsilon}$	τ_{GD,r_s^2}
Wallace et al. (2006).	5	Accidents	0.80	1.00	0.40	0.80	0.80	1.00	0.80
Walters et al. (2010).	16	holding period returns	0.77	1.00	0.57	0.63	0.73	1.00	0.77
Walters et al. (2010).	17	holding period returns	0.78	1.00	0.56	0.76	0.74	0.97	0.75
Zhang & Peterson (2011).	7	Team performance	1.00	1.00	0.62	0.81	0.81	1.00	1.00
Zhang & Peterson (2011).	6	Advice network density	1.00	1.00	0.87	0.60	0.87	1.00	1.00

Article	Number of Predictors	Dependent Variable	$\tau_{GD,U}$	$\tau_{GD,C}$	$\tau_{GD,\boldsymbol{m}}$	τ_{ϵ,r_s^2}	$\tau_{\epsilon,U}$	$\tau_{\epsilon,C}$	$\tau_{\epsilon,\boldsymbol{m}}$
Agle et al. (2006).	3	CEO charisma	0.33	0.33	0.33	1.00	1.00	-0.33	0.33
Agle et al. (2006).	3	CEO charisma	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Agle et al. (2006).	3	CEO charisma	1.00	0.33	1.00	1.00	1.00	0.33	1.00
Agle et al. (2006).	3	CEO charisma	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Agle et al. (2006).	3	CEO charisma	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Agle et al. (2006).	3	CEO charisma	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Anderson et al. (2008).	12	Influence	0.64	0.76	0.82	0.79	0.79	0.39	0.82

Article	Number of Predictors	Dependent Variable	$\tau_{GD,U}$	$\tau_{GD,C}$	$\tau_{GD,\boldsymbol{m}}$	τ_{ϵ,r_s^2}	$\tau_{\epsilon,U}$	$\tau_{\epsilon,C}$	$\tau_{\epsilon,\boldsymbol{m}}$
Anderson et al. (2008).	12	Influence	0.76	0.61	0.85	0.85	0.85	0.67	0.82
Aryee et al. (2012).	5	Branch market performance	0.40	0.40	1.00	0.80	0.80	0.20	1.00
Austin (2003).	5	Goal attainment	0.60	1.00	0.60	0.80	0.80	0.60	0.80
Austin (2003).	5	Ext evaluation	0.80	0.80	1.00	1.00	1.00	0.60	1.00
Austin (2003).	5	Internal evaluation	0.20	1.00	0.60	1.00	1.00	0.20	0.60
Balkundi et al. (2011).	8	Team performance	1.00	0.57	0.86	0.71	0.71	0.57	0.86
Balkundi et al. (2011).	7	Leader charisma	0.71	0.62	0.81	0.71	0.71	0.52	0.71
Balkundi et al. (2011).	7	Leader centrality	0.52	0.43	0.81	0.62	0.62	-0.05	0.81

Article	Number of Predictors	Dependent Variable	$\tau_{GD,U}$	$\tau_{GD,C}$	$\tau_{GD,m}$	τ_{ϵ,r_s^2}	$\tau_{\epsilon,U}$	$\tau_{\epsilon,C}$	$\tau_{\epsilon,m}$
Balkundi et al. (2011).	6	Leader charisma (T2)	0.47	0.20	0.73	0.87	0.87	0.20	0.73
Balkundi et al. (2011).	6	Leader centrality (T2)	0.20	0.47	0.87	1.00	1.00	0.20	0.87
Balkundi et al. (2011).	8	Team performance (T3)	0.57	0.43	0.64	0.64	0.64	0.14	0.64
Bansal & Clelland (2004).	11	Unsystematic risk	0.75	0.56	0.75	0.71	0.71	0.38	0.71
Barnes et al.(2008).	3	Team performance	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Barnett & King (2008).	5	cumulative abnormal return	0.80	0.40	1.00	0.80	0.80	0.60	1.00
Barnett & King (2008).	3	cumulative abnormal return	1.00	0.33	1.00	1.00	1.00	0.33	1.00

Article	Number of Predictors	Dependent Variable	$\tau_{GD,U}$	$\tau_{GD,C}$	$\tau_{GD,\boldsymbol{m}}$	τ_{ϵ,r_s^2}	$\tau_{\epsilon,U}$	$\tau_{\epsilon,C}$	$\tau_{\epsilon,\boldsymbol{m}}$
Barrick et al. (2010).	4	Interview score	0.33	1.00	0.67	0.67	0.67	0.33	1.00
Barrick et al. (2010).	4	Interview score (structured only; in Interview 3)	1.00	0.67	1.00	1.00	1.00	0.67	1.00
Barrick et al. (2010).	4	Second interview	0.67	0.00	0.67	0.33	0.33	-0.33	1.00
Bell et al. (2006).	5	Procedural justice expectations (1)	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Bell et al. (2006).	5	Distributive justice expectations (1)	1.00	0.20	1.00	0.80	0.80	0.20	1.00

Article	Number of Predictors	Dependent Variable	$\tau_{GD,U}$	$\tau_{GD,C}$	$\tau_{GD,\boldsymbol{m}}$	τ_{ϵ,r_s^2}	$\tau_{\epsilon,U}$	$\tau_{\epsilon,C}$	$\tau_{\epsilon,\boldsymbol{m}}$
Bell et al. (2006).	5	Interpersonal justice expectations (1)	1.00	0.80	1.00	0.80	0.80	0.80	1.00
Bell et al. (2006).	5	Informational justice expectations (1)	1.00	1.00	1.00	0.40	0.40	1.00	1.00
Bell et al. (2006).	9	Test-taking efficacy (1)	0.72	0.89	1.00	1.00	1.00	0.72	1.00
Bell et al. (2006).	9	Test-taking motivation (1)	0.83	0.72	0.94	0.83	0.83	0.56	0.94
Bell et al. (2006).	9	Intention to accept job (1)	0.78	0.83	0.89	0.78	0.78	0.72	0.83
Bell et al. (2006).	9	Intention to recommend job (1)	1.00	0.78	1.00	0.83	0.83	0.78	1.00

Article	Number of Predictors	Dependent Variable	$\tau_{GD,U}$	$\tau_{GD,C}$	$\tau_{GD,\boldsymbol{m}}$	$\tau_{\boldsymbol{\epsilon},\boldsymbol{r_s^2}}$	$\tau_{\boldsymbol{\epsilon},U}$	$\tau_{\boldsymbol{\epsilon},C}$	$\tau_{\boldsymbol{\epsilon},\boldsymbol{m}}$
Bell et al. (2006).	10	Procedural justice perceptions (2)	0.33	0.56	0.69	0.91	0.91	0.07	0.69
Bell et al. (2006).	10	Distributive justice perceptions (2)	0.56	0.69	0.82	0.87	0.87	0.42	0.82
Bell et al. (2006).	10	Interpersonal justice perceptions (2)	0.47	0.82	0.73	0.82	0.82	0.47	0.78
Bell et al. (2006).	10	Informational justice perceptions (2)	0.64	0.73	1.00	0.82	0.82	0.47	0.91
Bernerth et al. (2012).	5	FICO	1.00	0.60	1.00	0.80	0.80	0.60	1.00

Article	Number of Predictors	Dependent Variable	$\tau_{GD,U}$	$\tau_{GD,C}$	$\tau_{GD,m}$	τ_{ϵ,r_s^2}	$\tau_{\epsilon,U}$	$\tau_{\epsilon,C}$	$\tau_{\epsilon,m}$
Bordia et al. (2008).	4	Minor offenses (Time 2)	1.00	1.00	0.33	0.33	0.33	1.00	0.33
Bordia et al. (2008).	4	Major offenses (Time 2)	1.00	0.67	0.67	1.00	1.00	0.67	1.00
Brett & Stroh (2003).	20	Work hours	0.52	0.52	0.82	0.73	0.73	0.26	0.76
Brett & Stroh (2003).	20	Work hours	0.51	0.64	0.79	0.78	0.78	0.19	0.78
Brown & Treviño (2009).	6	Self-enhancement (E)	0.87	-0.07	0.73	0.87	0.87	0.07	0.87
Brown & Treviño (2009).	6	Openness to change (E)	0.60	0.20	1.00	0.87	0.87	0.07	1.00
Brown & Treviño (2009).	6	Conservation (E)	0.60	0.60	0.73	0.73	0.73	0.20	0.73

Article	Number of Predictors	Dependent Variable	$\tau_{GD,U}$	$\tau_{GD,C}$	$\tau_{GD,\boldsymbol{m}}$	τ_{ϵ,r_s^2}	$\tau_{\epsilon,U}$	$\tau_{\epsilon,C}$	$\tau_{\epsilon,\boldsymbol{m}}$
Brown & Treviño (2009).	5	Self-enhancement (L)	0.60	0.60	0.60	1.00	1.00	0.20	0.60
Brown & Treviño (2009).	5	Openness to change (L)	1.00	1.00	1.00	0.80	0.80	1.00	1.00
Brown & Treviño (2009).	5	Conservation (L)	0.80	0.80	1.00	1.00	1.00	1.00	1.00
Brown & Treviño (2006).	4	Organizational deviance	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Brown & Treviño (2006).	4	Values congruence	1.00	0.67	1.00	0.67	0.67	0.67	1.00
Brown & Treviño (2006).	4	Interpersonal deviance	1.00	0.67	1.00	1.00	1.00	0.67	1.00
Brown & Treviño (2006).	5	Organizational deviance	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Article	Number of Predictors	Dependent Variable	$\tau_{GD,U}$	$\tau_{GD,C}$	$\tau_{GD,\boldsymbol{m}}$	$\tau_{\boldsymbol{\epsilon},\boldsymbol{r_s^2}}$	$\tau_{\boldsymbol{\epsilon},U}$	$\tau_{\epsilon,C}$	$\tau_{\boldsymbol{\epsilon},\boldsymbol{m}}$
Carton et al.(2014).	20	heart attack readmission prevention	0.31	0.69	0.52	0.65	0.65	0.27	0.52
Carton et al.(2014).	18	heart attack readmission prevention	0.37	0.79	0.42	0.66	0.66	0.40	0.45
Charles et al.(2013).	7	Wave 2 general affective distress	0.90	0.71	1.00	0.81	0.81	0.62	1.00
Charles et al.(2013).	6	Wave 2 general affective distress	0.87	0.73	1.00	0.87	0.87	0.60	1.00
Charles et al.(2013).	6	Wave 2 general affective distress	0.87	0.47	0.87	0.87	0.87	0.33	0.87
Chen et al.(2011).	4	Psychological empowerment	0.67	-0.33	1.00	1.00	1.00	0.00	1.00

Article	Number of Predictors	Dependent Variable	$\tau_{GD,U}$	$\tau_{GD,C}$	$\tau_{GD,\boldsymbol{m}}$	$\tau_{\boldsymbol{\epsilon},\boldsymbol{r_s^2}}$	$\tau_{\boldsymbol{\epsilon},U}$	$\tau_{\boldsymbol{\epsilon},C}$	$\tau_{\boldsymbol{\epsilon},\boldsymbol{m}}$
Chen et al.(2011).	4	Affective commitment	1.00	0.67	1.00	1.00	1.00	0.67	1.00
Chen et al.(2005).	3	Transition processes	1.00	0.33	1.00	0.33	0.33	0.33	1.00
Chen et al.(2005).	4	Action processes	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Chen et al.(2005).	5	Team adaptive performance	0.80	0.20	1.00	0.60	0.60	0.00	1.00
Christmann (2004).	8	Level of internal global environmental performance standards	0.64	0.36	0.71	0.79	0.79	0.14	0.71

Article	Number of Predictors	Dependent Variable	$\tau_{GD,U}$	$\tau_{GD,C}$	$\tau_{GD,\boldsymbol{m}}$	$\tau_{\boldsymbol{\epsilon},\boldsymbol{r_s^2}}$	$\tau_{\epsilon,U}$	$\tau_{\epsilon,C}$	$\tau_{\boldsymbol{\epsilon},\boldsymbol{m}}$
Christmann (2004).	8	Global operational environmental policy standardization	0.57	0.79	0.86	0.93	0.93	0.36	0.93
Christmann (2004).	8	Global environmental communication standardization	0.79	0.43	0.64	0.79	0.79	0.21	0.64
Conlon et al. (2006).	8	Logged Citations	0.79	0.29	0.86	0.64	0.64	0.36	0.86
Conlon et al. (2006).	10	Logged Citations	0.73	0.56	0.82	0.38	0.38	0.56	0.73
Courtright et al. (2014).	4	Engagement	1.00	0.67	1.00	1.00	1.00	0.67	1.00

Article	Number of Predictors	Dependent Variable	$\tau_{GD,U}$	$\tau_{GD,C}$	$\tau_{GD,m}$	τ_{ϵ,r_s^2}	$\tau_{\epsilon,U}$	$\tau_{\epsilon,C}$	$\tau_{\epsilon,m}$
Courtright et al. (2014).	5	Emotional exhaustion	0.60	1.00	1.00	1.00	1.00	0.60	1.00
Courtright et al. (2014).	6	Transformational leadership	0.60	0.33	0.87	1.00	1.00	-0.07	0.87
Courtright et al. (2014).	6	Laissez faire leadership	0.87	0.33	0.33	0.33	0.33	0.47	0.33
Cross & Cummings (2004).	11	Performance	0.53	0.45	0.78	0.82	0.82	0.05	0.78
Cross & Cummings (2004).	11	Performance	0.60	0.71	0.93	0.85	0.85	0.31	0.93
Curhan, Elfenbein & Kilduff (2009).	11	Compensation satisfaction	0.82	0.31	0.89	0.75	0.75	0.20	0.96

Article	Number of Predictors	Dependent Variable	$\tau_{GD,U}$	$\tau_{GD,C}$	$\tau_{GD,m}$	τ_{ϵ,r_s^2}	$\tau_{\epsilon,U}$	$\tau_{\epsilon,C}$	$\tau_{\epsilon,m}$
Curhan, Elfenbein & Kilduff (2009).	11	Job satisfaction	0.75	0.42	0.82	0.78	0.78	0.31	0.75
Curhan, Elfenbein & Kilduff (2009).	11	Turnover intention	0.71	0.56	0.75	0.82	0.82	0.35	0.75
Dabos & Rousseau (2004).	3	Scientist Transactional (S)	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Dabos & Rousseau (2004).	3	Scientist Relational (S)	1.00	0.33	1.00	1.00	1.00	0.33	1.00
Dabos & Rousseau (2004).	3	Scientist Balanced (S)	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Article	Number of Predictors	Dependent Variable	$\tau_{GD,U}$	$\tau_{GD,C}$	$\tau_{GD,\boldsymbol{m}}$	τ_{ϵ,r_s^2}	$\tau_{\epsilon,U}$	$\tau_{\epsilon,C}$	$\tau_{\epsilon,\boldsymbol{m}}$
Dabos & Rousseau (2004).	3	Director Transactional (S)	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Dabos & Rousseau (2004).	3	Director Relational (S)	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Dabos & Rousseau (2004).	3	Director Balanced (S)	1.00	0.33	1.00	1.00	1.00	0.33	1.00
Davidson et al. (2004).	7	Discretionary current accruals	0.90	0.62	0.90	0.71	0.71	0.52	0.90
Davidson et al. (2004).	6	Discretionary current accruals	0.87	0.20	0.87	0.60	0.60	0.07	0.87
Davidson et al. (2004).	5	Discretionary current accruals	1.00	0.60	1.00	0.60	0.60	0.60	1.00

Article	Number of Predictors	Dependent Variable	$\tau_{GD,U}$	$\tau_{GD,C}$	$\tau_{GD,\boldsymbol{m}}$	$\tau_{\boldsymbol{\epsilon},\boldsymbol{r_s^2}}$	$\tau_{\epsilon,U}$	$\tau_{\epsilon,C}$	$\tau_{\boldsymbol{\epsilon},\boldsymbol{m}}$
de Jong et al. (2014).	4	team performance	1.00	1.00	0.67	0.67	0.67	1.00	0.67
de Vries et al.(2014).	4	interteam coordination	0.67	0.00	1.00	1.00	1.00	-0.33	1.00
de Vries et al.(2014).	3	cognitive complexity	1.00	1.00	1.00	1.00	1.00	1.00	1.00
de Vries et al.(2014).	5	interteam coordination	0.80	0.20	1.00	1.00	1.00	0.00	1.00
DeChurch & Marks (2006).	3	Interteam coordination (explicit)	1.00	-0.33	0.33	0.33	0.33	-0.33	0.33
DeChurch & Marks (2006).	3	Interteam coordination (implicit)	0.33	-0.33	1.00	-0.33	-0.33	-1.00	1.00

Article	Number of Predictors	Dependent Variable	$\tau_{GD,U}$	$\tau_{GD,C}$	$\tau_{GD,m}$	τ_{ϵ,r_s^2}	$\tau_{\epsilon,U}$	$\tau_{\epsilon,C}$	$\tau_{\epsilon,m}$
DeChurch & Marks (2006).	3	Interteam coordination (explicit)	1.00	1.00	1.00	1.00	1.00	1.00	1.00
DeChurch & Marks (2006).	3	Interteam coordination (implicit)	0.33	1.00	0.33	1.00	1.00	0.33	0.33
DeChurch & Marks (2006).	4	MTS performance	0.00	0.67	1.00	1.00	1.00	-0.33	1.00
DeChurch & Marks (2006).	4	MTS performance	0.67	0.67	1.00	1.00	1.00	0.33	1.00
DeChurch & Marks (2006).	4	MTS performance	1.00	0.67	1.00	1.00	1.00	0.67	0.67
DeChurch & Marks (2006).	4	MTS performance	0.67	0.67	1.00	1.00	1.00	0.33	1.00

Article	Number of Predictors	Dependent Variable	$\tau_{GD,U}$	$\tau_{GD,C}$	$\tau_{GD,m}$	τ_{ϵ,r_s^2}	$\tau_{\epsilon,U}$	$\tau_{\epsilon,C}$	$\tau_{\epsilon,m}$
DeChurch & Marks (2006).	5	MTS performance	1.00	0.20	1.00	0.80	0.80	0.20	1.00
DeChurch & Marks (2006).	5	MTS performance	0.80	0.60	1.00	1.00	1.00	0.40	1.00
DeChurch et al. (2013).	5	Performance	0.80	0.80	1.00	1.00	1.00	0.60	1.00
DeChurch et al. (2013).	5	Affective outcomes	0.80	0.80	0.80	1.00	1.00	0.60	0.80
DeChurch et al. (2013).	3	Performance	0.33	1.00	1.00	1.00	1.00	0.33	1.00
DeChurch et al. (2013).	3	Affective outcomes	1.00	1.00	1.00	1.00	1.00	1.00	1.00
DeRue & Morgeson (2007).	3	Person–role fit (Time 5)	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Article	Number of Predictors	Dependent Variable	$\tau_{GD,U}$	$\tau_{GD,C}$	$\tau_{GD,\boldsymbol{m}}$	τ_{ϵ,r_s^2}	$\tau_{\epsilon,U}$	$\tau_{\epsilon,C}$	$\tau_{\epsilon,\boldsymbol{m}}$
DeRue et al. (2008).	6	team performance	0.73	0.20	0.87	0.73	0.73	0.20	0.87
Detert et al. (2008).	10	Moral disengagement	0.91	0.24	0.87	0.73	0.73	0.24	0.87
Detert et al. (2008).	11	Unethical decisions	0.75	0.64	0.93	0.71	0.71	0.45	0.93
Detert et al. (2007).	15	Operating profit	0.47	0.83	0.77	0.81	0.81	0.30	0.77
Detert et al. (2007).	15	Customer Satisfaction	0.60	0.62	0.85	0.75	0.75	0.60	0.89
Detert et al. (2007).	14	Food loss	0.71	0.56	0.85	0.80	0.80	0.41	0.80
Dierdorff & Morgeson (2007).	6	Task requirements	0.73	0.33	1.00	0.87	0.87	0.60	1.00

Article	Number of Predictors	Dependent Variable	$\tau_{GD,U}$	$\tau_{GD,C}$	$\tau_{GD,\boldsymbol{m}}$	$\tau_{\boldsymbol{\epsilon},\boldsymbol{r_s^2}}$	$\tau_{\boldsymbol{\epsilon},U}$	$\tau_{\epsilon,C}$	$\tau_{\boldsymbol{\epsilon},\boldsymbol{m}}$
Dierdorff & Morgeson (2007).	6	Responsibility requirements	0.47	0.73	0.73	0.60	0.60	0.20	0.73
Dierdorff & Morgeson (2007).	6	Trait requirements	0.47	0.60	0.73	1.00	1.00	0.07	0.73
Drescher et al. (2014).	6	trusting behavior change	0.33	1.00	0.73	1.00	1.00	0.33	0.73
Drescher et al. (2014).	6	trusting behavior time 3	1.00	0.47	1.00	0.60	0.60	0.47	1.00
Duffy et al. (2012).	8	Social undermining, time 2	0.86	0.21	0.93	0.79	0.79	0.07	0.93

Article	Number of Predictors	Dependent Variable	$\tau_{GD,U}$	$\tau_{GD,C}$	$\tau_{GD,\boldsymbol{m}}$	τ_{ϵ,r_s^2}	$\tau_{\epsilon,U}$	$\tau_{\epsilon,C}$	$\tau_{\epsilon,\boldsymbol{m}}$
Eby et al. (2008).	9	Protege intentions to leave the relationship	0.44	0.56	0.78	0.89	0.89	0.00	0.78
Eby et al. (2008).	9	Protege receipt of career-related mentoring	0.50	0.78	0.72	0.78	0.78	0.28	0.67
Eby et al. (2008).	9	Protege receipt of psychosocial mentoring	0.50	0.78	0.50	0.89	0.89	0.28	0.56
Eby et al. (2008).	9	Mentor intentions to leave the relationship	0.39	0.78	0.67	0.67	0.67	0.17	0.72

Article	Number of Predictors	Dependent Variable	$\tau_{GD,U}$	$\tau_{GD,C}$	$\tau_{GD,\boldsymbol{m}}$	$\tau_{\boldsymbol{\epsilon},\boldsymbol{r_s^2}}$	$\tau_{\epsilon,U}$	$\tau_{\epsilon,C}$	$\tau_{\boldsymbol{\epsilon},\boldsymbol{m}}$
Eby et al. (2008).	9	Mentor burnout	0.61	0.33	0.44	0.28	0.28	0.06	0.44
Edwards et al. (2006).	3	Average team performanc	0.33	0.33	0.33	1.00	1.00	-0.33	0.33
Edwards et al. (2006).	3	Average team performanc	1.00	0.33	0.33	1.00	1.00	0.33	0.33
Firth et al. (2014).	8	initial work adjustment	0.71	0.86	0.93	0.93	0.93	0.57	1.00
Firth et al. (2014).	9	work adjustment change	0.67	0.78	0.83	0.78	0.78	0.56	0.83
Firth et al. (2014).	10	premature return intention	0.64	0.47	0.82	0.73	0.73	0.56	0.78
Firth et al. (2014).	10	job satisfaction	0.73	0.91	0.82	0.69	0.69	0.64	0.91

Article	Number of Predictors	Dependent Variable	$\tau_{GD,U}$	$\tau_{GD,C}$	$\tau_{GD,m}$	τ_{ϵ,r_s^2}	$\tau_{\epsilon,U}$	$\tau_{\epsilon,C}$	$\tau_{\epsilon,m}$
Fisher (2014).	5	Coordination	0.60	1.00	0.40	0.40	0.40	0.60	0.40
Fisher (2014).	5	Interpersonal processes	0.40	0.60	0.40	0.80	0.80	0.00	0.40
Fisher (2014).	5	Coordination	1.00	1.00	0.40	0.40	0.40	1.00	0.40
Fisher (2014).	5	Interpersonal processes	0.60	0.40	0.60	0.80	0.80	0.00	0.60
Fisher et al. (2012).	7	TMM similarity	1.00	0.81	0.90	0.62	0.62	0.81	0.81
Fisher et al. (2012).	4	Implicit coordination	1.00	1.00	0.67	0.33	0.33	1.00	0.67
Fisher et al. (2012).	4	Team performance	1.00	-0.33	0.33	1.00	1.00	-0.33	0.33
Flynn & Brockner (2003).	6	Commitment	0.73	0.73	0.73	0.73	0.73	0.47	0.87

Article	Number of Predictors	Dependent Variable	$\tau_{GD,U}$	$\tau_{GD,C}$	$\tau_{GD,m}$	τ_{ϵ,r_s^2}	$\tau_{\epsilon,U}$	$\tau_{\epsilon,C}$	$\tau_{\epsilon,m}$
Flynn & Brockner (2003).	6	Commitment	0.73	0.73	0.87	0.87	0.87	0.47	0.87
Flynn & Brockner (2003).	6	Commitment	0.60	0.47	0.47	0.87	0.87	0.07	0.47
Flynn & Brockner (2003).	6	Commitment	0.60	0.73	0.73	0.87	0.87	0.33	0.73
Flynn & Schaumberg (2012).	3	Affective commitment	1.00	0.33	1.00	1.00	1.00	0.33	1.00
Flynn & Schaumberg (2012).	4	Affective commitment	0.67	0.67	1.00	1.00	1.00	1.00	1.00

Article	Number of Predictors	Dependent Variable	$\tau_{GD,U}$	$\tau_{GD,C}$	$\tau_{GD,m}$	τ_{ϵ,r_s^2}	$\tau_{\epsilon,U}$	$\tau_{\epsilon,C}$	$\tau_{\epsilon,m}$
Flynn & Schaumberg (2012).	4	Work effort	1.00	0.67	1.00	1.00	1.00	0.67	1.00
Flynn & Schaumberg (2012).	8	Affective commitment	0.79	-0.07	0.79	0.57	0.57	-0.29	0.86
Flynn & Schaumberg (2012).	8	Work effort	0.57	0.57	1.00	1.00	1.00	0.29	1.00
Fritz & Sonnentag (2006).	12	health complaints t3	0.58	0.70	0.79	0.67	0.67	0.27	0.76
Fritz & Sonnentag (2006).	12	health complaints t4	0.27	0.85	0.67	0.79	0.79	0.18	0.64

Article	Number of Predictors	Dependent Variable	$\tau_{GD,U}$	$\tau_{GD,C}$	$\tau_{GD,m}$	τ_{ϵ,r_s^2}	$\tau_{\epsilon,U}$	$\tau_{\epsilon,C}$	$\tau_{\epsilon,m}$
Fritz & Sonnentag (2006).	12	Exhaustion T3	0.58	0.79	0.82	0.85	0.85	0.42	0.85
Fritz & Sonnentag (2006).	12	Exhaustion T4	0.73	0.88	0.79	0.70	0.70	0.61	0.82
Fritz & Sonnentag (2006).	12	Disengagement T3	0.42	0.76	0.88	0.85	0.85	0.24	0.91
Fritz & Sonnentag (2006).	12	Disengagement T4	0.55	0.79	0.76	0.79	0.79	0.39	0.73
Fritz & Sonnentag (2006).	12	Task performance T3	0.58	0.24	0.91	0.82	0.82	0.24	0.94

Article	Number of Predictors	Dependent Variable	$\tau_{GD,U}$	$\tau_{GD,C}$	$\tau_{GD,m}$	τ_{ϵ,r_s^2}	$\tau_{\epsilon,U}$	$\tau_{\epsilon,C}$	$\tau_{\epsilon,m}$
Fritz & Sonnentag (2006).	12	Task performance T4	0.67	0.48	0.85	0.55	0.55	0.15	0.88
Fritz & Sonnentag (2006).	12	Effort expenditure T3	0.79	0.52	0.91	0.73	0.73	0.42	0.85
Fritz & Sonnentag (2006).	12	Effort expenditure T4	0.58	0.48	0.88	0.58	0.58	0.36	0.88
Fritz et al. (2010).	9	Exhaustion	0.78	0.78	0.94	0.94	0.94	0.67	0.94
Fritz et al. (2010).	9	Life satisfaction	0.72	0.83	0.94	0.83	0.83	0.56	0.94

Article	Number of Predictors	Dependent Variable	$\tau_{GD,U}$	$\tau_{GD,C}$	$\tau_{GD,m}$	τ_{ϵ,r_s^2}	$\tau_{\epsilon,U}$	$\tau_{\epsilon,C}$	$\tau_{\epsilon,m}$
Gardner et al. (2012).	9	Knowledge integration capability	0.78	0.72	0.83	0.78	0.78	0.61	0.83
Glebbeek & Bax (2004).	4	Net Result, 1995–98	1.00	0.67	0.67	0.33	0.33	0.67	0.67
Glebbeek & Bax (2004).	3	Net Result, 1995–98	1.00	0.33	1.00	1.00	1.00	0.33	1.00
Glebbeek & Bax (2004).	4	Net Result, 1997–98	1.00	0.67	1.00	1.00	1.00	0.67	1.00
Glebbeek & Bax (2004).	3	Net Result, 1997–98	1.00	-0.33	1.00	1.00	1.00	-0.33	1.00
Glebbeek & Bax (2004).	5	Net Result, 1996–98	0.80	0.40	1.00	1.00	1.00	0.60	1.00
Glebbeek & Bax (2004).	4	Net Result, 1996–98	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Article	Number of Predictors	Dependent Variable	$\tau_{GD,U}$	$\tau_{GD,C}$	$\tau_{GD,\boldsymbol{m}}$	$\tau_{\boldsymbol{\epsilon},\boldsymbol{r_s^2}}$	$\tau_{\boldsymbol{\epsilon},U}$	$\tau_{\boldsymbol{\epsilon},C}$	$\tau_{\boldsymbol{\epsilon},\boldsymbol{m}}$
Glebbeek & Bax (2004).	5	Net Result, 1997–98	0.80	0.20	1.00	1.00	1.00	0.40	1.00
Glebbeek & Bax (2004).	4	Net Result, 1997–98	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Gong et al. (2009).	14	Firm performance	0.56	0.52	0.74	0.71	0.71	0.25	0.69
Gong et al. (2009).	12	Affective commitment	0.73	0.52	0.82	0.88	0.88	0.30	0.82
Gong et al. (2009).	12	Continuance commitment	0.45	0.67	0.85	0.82	0.82	0.42	0.88
Gonzalez-Mulé et al. (2014).	5	cooperative group norms	0.80	0.60	1.00	0.80	0.80	0.40	1.00
Gonzalez-Mulé et al. (2014).	6	cwb	0.73	0.20	0.73	0.73	0.73	0.47	0.73

Article	Number of Predictors	Dependent Variable	$\tau_{GD,U}$	$\tau_{GD,C}$	$\tau_{GD,m}$	τ_{ϵ,r_s^2}	$\tau_{\epsilon,U}$	$\tau_{\epsilon,C}$	$\tau_{\epsilon,m}$
Gonzalez-Mulé et al. (2014).	6	ocb	0.87	-0.20	1.00	1.00	1.00	-0.33	1.00
Gonzalez-Mulé et al. (2014).	6	task performance	0.60	0.60	0.47	1.00	1.00	0.20	0.60
Gonzalez-Mulé et al. (2014).	6	job performance	0.87	0.33	0.87	0.87	0.87	0.47	0.87
Gupta et al. (2013).	6	Sales performance	0.87	0.47	1.00	1.00	1.00	0.60	1.00
Gupta et al. (2013).	6	Performance appraisal	1.00	0.33	0.87	0.87	0.87	0.33	0.87
Gupta et al. (2013).	7	Sales performance	1.00	0.24	0.90	0.71	0.71	0.24	0.81
Gupta et al. (2013).	7	Performance appraisal	0.62	0.52	0.90	0.81	0.81	0.33	0.90

Article	Number of Predictors	Dependent Variable	$\tau_{GD,U}$	$\tau_{GD,C}$	$\tau_{GD,\boldsymbol{m}}$	$\tau_{\boldsymbol{\epsilon},\boldsymbol{r_s^2}}$	$\tau_{\boldsymbol{\epsilon},U}$	$\tau_{\boldsymbol{\epsilon},C}$	$\tau_{\boldsymbol{\epsilon},\boldsymbol{m}}$
Gupta et al. (2013).	4	Sales at Month 1	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Gupta et al. (2013).	4	Sales at Month 2	1.00	1.00	1.00	0.67	0.67	1.00	1.00
Gupta et al. (2013).	4	Sales at Month 3	0.33	-0.33	1.00	1.00	1.00	0.33	1.00
Gupta et al. (2013).	4	Sales at Month 4	0.33	-0.33	1.00	1.00	1.00	-0.33	1.00
Gupta et al. (2013).	4	Sales at Month 5	0.67	0.67	1.00	1.00	1.00	0.33	1.00
Gupta et al. (2013).	5	Sales at Month 1	1.00	1.00	1.00	0.20	0.20	1.00	1.00
Gupta et al. (2013).	5	Sales at Month 2	1.00	1.00	1.00	0.20	0.20	1.00	1.00

Article	Number of Predictors	Dependent Variable	$\tau_{GD,U}$	$\tau_{GD,C}$	$\tau_{GD,\boldsymbol{m}}$	τ_{ϵ,r_s^2}	$\tau_{\epsilon,U}$	$\tau_{\epsilon,C}$	$\tau_{\epsilon,\boldsymbol{m}}$
Gupta et al. (2013).	5	Sales at Month 3	0.60	0.20	0.80	1.00	1.00	0.60	0.80
Gupta et al. (2013).	5	Sales at Month 4	0.60	0.40	1.00	0.60	0.60	0.40	1.00
Gupta et al. (2013).	5	Sales at Month 5	0.60	0.20	0.60	1.00	1.00	-0.20	1.00
Hannah et al. (2013).	4	Adaptive decision-making	0.33	0.67	0.67	0.33	0.33	0.00	1.00
Harris et al. (2008).	8	Pay level satisfaction	0.79	0.07	0.43	0.36	0.36	0.29	0.43
Hay et al. (2011).	4	Parental reports of infance aggressiveness	0.67	1.00	1.00	1.00	1.00	0.67	1.00

Article	Number of Predictors	Dependent Variable	$\tau_{GD,U}$	$\tau_{GD,C}$	$\tau_{GD,m}$	τ_{ϵ,r_s^2}	$\tau_{\epsilon,U}$	$\tau_{\epsilon,C}$	$\tau_{\epsilon,m}$
Hay et al. (2011).	4	Observed use of instrumental force	0.67	0.67	0.67	0.67	0.67	0.33	0.67
Hay et al. (2011).	4	Observed use of bodily force	1.00	1.00	1.00	0.67	0.67	1.00	1.00
Heimeriks et al. (2012).	11	Acquisition integration performance	0.60	0.71	0.93	0.85	0.85	0.31	0.85
Heimeriks et al. (2012).	11	Risk management practices	0.53	0.75	0.78	0.71	0.71	0.35	0.71
Hewlin (2009).	4	Nonparticipative environments	0.67	0.00	1.00	1.00	1.00	-0.33	1.00

Article	Number of Predictors	Dependent Variable	$\tau_{GD,U}$	$\tau_{GD,C}$	$\tau_{GD,m}$	τ_{ϵ,r_s^2}	$\tau_{\epsilon,U}$	$\tau_{\epsilon,C}$	$\tau_{\epsilon,m}$
Hinkin & Schriesheim (2008).	4	Supervisor effectiveness	1.00	-0.33	1.00	0.00	0.00	-0.33	1.00
Hinkin & Schriesheim (2008).	4	Supervisor satisfaction	0.67	0.67	0.67	0.33	0.33	0.33	1.00
Hinkin & Schriesheim (2008).	3	Role clarity	1.00	0.33	1.00	1.00	1.00	0.33	1.00
Hirschfeld et al. (2013).	6	Within-team participation rate	0.60	0.33	1.00	0.60	0.60	-0.07	1.00
Hirschfeld et al. (2013).	10	Observed teamwork effectiveness	0.47	0.73	0.82	0.78	0.78	0.20	0.87

Article	Number of Predictors	Dependent Variable	$\tau_{GD,U}$	$\tau_{GD,C}$	$\tau_{GD,\boldsymbol{m}}$	$\tau_{\boldsymbol{\epsilon},\boldsymbol{r_s^2}}$	$\tau_{\epsilon,U}$	$\tau_{\epsilon,C}$	$\tau_{\boldsymbol{\epsilon},\boldsymbol{m}}$
Hirschfeld & Bernerth (2008).	4	Team mental efficacy	1.00	0.67	1.00	1.00	1.00	0.67	1.00
Hirschfeld & Bernerth (2008).	4	Team physical efficacy	1.00	0.00	1.00	1.00	1.00	0.00	1.00
Hirschfeld & Bernerth (2008).	8	Project X Phase 2 results	0.50	0.57	0.71	0.79	0.79	0.07	0.71
Hirschfeld & Bernerth (2008).	8	Problem solving results	0.86	0.57	0.86	0.36	0.36	0.57	0.86
Hirschfeld & Bernerth (2008).	8	Field operations results	0.79	0.21	0.86	0.71	0.71	0.14	0.71
Hirschfeld & Bernerth (2008).	9	Internal social cohesion	0.44	0.83	0.67	0.72	0.72	0.28	0.67
Hirschfeld & Bernerth (2008).	10	Observed teamwork effectiveness	0.56	0.60	0.73	0.87	0.87	0.16	0.69

Article	Number of Predictors	Dependent Variable	$\tau_{GD,U}$	$\tau_{GD,C}$	$\tau_{GD,m}$	τ_{ϵ,r_s^2}	$\tau_{\epsilon,U}$	$\tau_{\epsilon,C}$	$\tau_{\epsilon,m}$
Hult et al. (2004).	3	Knowledge acquisition	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Hult et al. (2004).	4	Information distribution	0.33	1.00	0.67	1.00	1.00	0.33	0.67
Hult et al. (2004).	5	Shared meaning	0.40	1.00	1.00	1.00	1.00	0.40	1.00
Hult et al. (2004).	6	Subjective cycle time	0.73	0.33	0.73	1.00	1.00	0.07	0.60
Ilies & Judge (2003).	5	Job satisfaction	0.60	0.60	1.00	0.80	0.80	0.20	1.00
Jackson et al. (2006).	6	Citizenship behavior	0.87	0.20	1.00	0.87	0.87	0.33	1.00
Jackson et al. (2006).	6	Counter-productive behavior	0.73	0.47	1.00	0.73	0.73	0.73	1.00

Article	Number of Predictors	Dependent Variable	$\tau_{GD,U}$	$\tau_{GD,C}$	$\tau_{GD,m}$	τ_{ϵ,r_s^2}	$\tau_{\epsilon,U}$	$\tau_{\epsilon,C}$	$\tau_{\epsilon,m}$
Jackson et al. (2006).	6	Withdrawal behavior	0.87	-0.20	1.00	0.73	0.73	-0.07	1.00
Jackson et al. (2006).	4	Task Performance	1.00	0.67	1.00	1.00	1.00	0.67	1.00
Janssen & Van Yperen (2004).	6	In-role job performance	0.60	0.20	0.60	0.73	0.73	-0.20	0.73
Janssen & Van Yperen (2004).	6	Innovative job performance	0.87	0.47	0.73	0.87	0.87	0.33	0.73
Janssen & Van Yperen (2004).	6	Job satisfaction	0.87	0.87	1.00	0.87	0.87	0.73	1.00
Janssen & Van Yperen (2004).	5	Leader-member exchange	0.80	0.40	1.00	1.00	1.00	0.60	1.00
Jehn et al. (2010).	4	Group performance score	1.00	0.67	0.67	0.67	0.67	0.67	0.33

Article	Number of Predictors	Dependent Variable	$\tau_{GD,U}$	$\tau_{GD,C}$	$\tau_{GD,\boldsymbol{m}}$	$\tau_{\boldsymbol{\epsilon},\boldsymbol{r_s^2}}$	$\tau_{\epsilon,U}$	$\tau_{\epsilon,C}$	$\tau_{\boldsymbol{\epsilon},\boldsymbol{m}}$
Jehn et al. (2010).	4	Creativity	0.67	-0.67	1.00	1.00	1.00	-1.00	1.00
Jehn et al. (2010).	4	Group performance score	0.67	0.33	1.00	0.67	0.67	0.67	1.00
Jehn et al. (2010).	4	Creativity	0.67	0.67	1.00	0.67	0.67	0.33	1.00
Jiang et al. (2012).	3	Human Capital	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Jiang et al. (2012).	3	Employee Motivation	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Johnson, Morgeson, Ilgen, Meyer & Lloyd (2006).	6	Job satisfaction	0.87	0.87	1.00	1.00	1.00	0.73	1.00

Article	Number of Predictors	Dependent Variable	$\tau_{GD,U}$	$\tau_{GD,C}$	$\tau_{GD,m}$	τ_{ϵ,r_s^2}	$\tau_{\epsilon,U}$	$\tau_{\epsilon,C}$	$\tau_{\epsilon,m}$
Judge et al. (2007).	8	Work-related performance	0.86	0.21	0.86	0.57	0.57	0.07	0.93
Judge et al. (2007).	7	Work-related performance	0.81	0.14	0.90	0.62	0.62	-0.05	1.00
Judge et al.(2006).	6	Leadership—self	0.60	0.07	0.73	0.73	0.73	-0.33	0.73
Judge et al.(2006).	6	Leadership—other	0.60	0.20	0.73	0.47	0.47	-0.20	0.87
Judge et al.(2006).	6	Leadership—self	0.60	0.07	0.87	0.20	0.20	-0.33	1.00
Judge et al.(2006).	6	Leadership—other	0.60	0.07	0.87	0.33	0.33	0.20	0.87
Judge et al.(2006).	6	Workplace deviance—self	1.00	0.33	1.00	0.87	0.87	0.33	1.00

Article	Number of Predictors	Dependent Variable	$\tau_{GD,U}$	$\tau_{GD,C}$	$\tau_{GD,\boldsymbol{m}}$	τ_{ϵ,r_s^2}	$\tau_{\epsilon,U}$	$\tau_{\epsilon,C}$	$\tau_{\epsilon,\boldsymbol{m}}$
Judge et al.(2006).	6	Workplace deviance—other	1.00	0.20	1.00	0.87	0.87	0.20	1.00
Judge et al.(2006).	6	Contextual performance—self	0.60	0.87	0.73	1.00	1.00	0.47	0.73
Judge et al.(2006).	6	Contextual performance—other	0.87	0.60	1.00	0.60	0.60	0.47	0.87
Judge et al.(2006).	6	Task performance—self	0.73	0.60	1.00	0.87	0.87	0.33	1.00
Judge et al.(2006).	6	Task performance—other	0.87	0.73	1.00	0.73	0.73	0.87	1.00
Kim & Jensen (2014).	25	foreign box office performance	0.55	0.74	0.84	0.81	0.81	0.38	0.83

Article	Number of Predictors	Dependent Variable	$\tau_{GD,U}$	$\tau_{GD,C}$	$\tau_{GD,\boldsymbol{m}}$	$\tau_{\boldsymbol{\epsilon},\boldsymbol{r_s^2}}$	$\tau_{\boldsymbol{\epsilon},U}$	$\tau_{\boldsymbol{\epsilon},C}$	$\tau_{\boldsymbol{\epsilon},\boldsymbol{m}}$
Kim & Jensen (2014).	21	foreign box office performance	0.58	0.61	0.89	0.73	0.73	0.25	0.91
Kirkman et al. (2004).	3	Process improvement	1.00	0.33	1.00	1.00	1.00	0.33	1.00
Kirkman et al. (2004).	3	Team customer satisfaction	1.00	0.33	1.00	1.00	1.00	0.33	1.00
Klehe & Anderson (2007).	7	Typical Performance 1	0.71	0.81	0.90	0.81	0.81	0.52	0.90
Klehe & Anderson (2007).	9	Typical Performance 2	0.50	0.83	0.61	0.83	0.83	0.33	0.67

Article	Number of Predictors	Dependent Variable	$\tau_{GD,U}$	$\tau_{GD,C}$	$\tau_{GD,\boldsymbol{m}}$	$\tau_{\boldsymbol{\epsilon},\boldsymbol{r_s^2}}$	$\tau_{\boldsymbol{\epsilon},U}$	$\tau_{\boldsymbol{\epsilon},C}$	$\tau_{\boldsymbol{\epsilon},\boldsymbol{m}}$
Klehe & Anderson (2007).	5	Typical Performance 1	1.00	0.80	1.00	0.80	0.80	0.80	1.00
Klehe & Anderson (2007).	5	Typical Performance 2	0.80	0.40	1.00	0.80	0.80	0.20	1.00
Klehe & Anderson (2007).	3	Maximum Perforance	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Kraimer et al. (2012).	9	International Employee Identity	0.67	0.44	0.94	0.89	0.89	0.11	0.94
Kwong & Wong (2014).	5	escalation allocation	0.80	0.80	0.80	0.80	0.80	0.60	0.80

Article	Number of Predictors	Dependent Variable	$\tau_{GD,U}$	$\tau_{GD,C}$	$\tau_{GD,\boldsymbol{m}}$	τ_{ϵ,r_s^2}	$\tau_{\epsilon,U}$	$\tau_{\epsilon,C}$	$\tau_{\epsilon,\boldsymbol{m}}$
Kwong & Wong (2014).	4	escalation allocation	0.67	1.00	0.67	1.00	1.00	0.67	0.67
Lai et al. (2009).	3	Acceptance	1.00	-0.33	1.00	1.00	1.00	-0.33	1.00
Leavitt et al. (2012).	3	Sphere of concern	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Lee et al.(2014).	8	speed	0.86	0.43	0.86	0.93	0.93	0.29	0.86
Lee et al.(2014).	8	accuracy	0.79	0.57	1.00	0.79	0.79	0.36	1.00
Lee et al. (2004).	4	Performance (in-role)	1.00	0.67	0.67	0.33	0.33	0.67	0.67
Lee et al. (2004).	4	OCB (extra-role)	0.33	0.67	0.33	0.67	0.67	0.00	0.33
Lee et al. (2004).	4	Volitional absences	1.00	1.00	1.00	0.67	0.67	1.00	0.67

Article	Number of Predictors	Dependent Variable	$\tau_{GD,U}$	$\tau_{GD,C}$	$\tau_{GD,\boldsymbol{m}}$	τ_{ϵ,r_s^2}	$\tau_{\epsilon,U}$	$\tau_{\epsilon,C}$	$\tau_{\epsilon,\boldsymbol{m}}$
Lian et al. (2012).	8	interpersonal deviance at work	0.50	0.93	0.93	0.86	0.86	0.43	0.93
Lian et al. (2012).	8	interpersonal deviance at home	0.86	0.64	0.79	0.71	0.71	0.50	0.93
Lievens & Sackett (2012).	3	Internship performance	1.00	0.33	1.00	1.00	1.00	0.33	1.00
Lievens & Sackett (2012).	3	Job performance	1.00	0.33	1.00	1.00	1.00	0.33	1.00
Lim & Ployhart (2004).	5	Transformational leadership	0.80	0.60	1.00	0.60	0.60	0.40	1.00
Madjar et al.(2011).	21	Radical Creativity	0.68	0.57	0.84	0.74	0.74	0.40	0.88

Article	Number of Predictors	Dependent Variable	$\tau_{GD,U}$	$\tau_{GD,C}$	$\tau_{GD,m}$	τ_{ϵ,r_s^2}	$\tau_{\epsilon,U}$	$\tau_{\epsilon,C}$	$\tau_{\epsilon,m}$
Madjar et al.(2011).	21	Incremental Creativity	0.60	0.68	0.80	0.67	0.67	0.58	0.78
Madjar et al.(2011).	21	Routine performance	0.50	0.53	0.69	0.68	0.68	0.24	0.69
McDonald & Westphal (2010).	11	identification with corporate elite	0.60	0.67	0.82	0.78	0.78	0.27	0.78
Moon et al. (2008).	6	Taking charge	0.60	0.33	1.00	0.60	0.60	0.20	0.87
Moon et al. (2008).	6	Taking charge (cow)	1.00	0.60	0.87	0.73	0.73	0.60	0.87
Moon et al. (2008).	6	Taking charge (sup)	0.47	0.87	0.73	0.87	0.87	0.60	0.87
Mumford et al. (2008).	7	task role performance	0.90	0.24	1.00	0.62	0.62	0.33	1.00

Article	Number of Predictors	Dependent Variable	$\tau_{GD,U}$	$\tau_{GD,C}$	$\tau_{GD,\boldsymbol{m}}$	$\tau_{\boldsymbol{\epsilon},\boldsymbol{r_s^2}}$	$\tau_{\boldsymbol{\epsilon},U}$	$\tau_{\boldsymbol{\epsilon},C}$	$\tau_{\boldsymbol{\epsilon},\boldsymbol{m}}$
Mumford et al. (2008).	7	social role performance	0.62	0.62	0.90	1.00	1.00	0.81	1.00
Mumford et al. (2008).	7	overall team performance	1.00	0.43	1.00	0.71	0.71	0.43	1.00
Mumford et al. (2008).	9	task role performance	0.78	0.44	1.00	0.61	0.61	0.22	1.00
Mumford et al. (2008).	9	social role performance	0.50	0.67	0.94	0.94	0.94	0.39	0.94
Mumford et al. (2008).	9	overall team performance	0.61	0.44	0.94	0.67	0.67	0.17	0.89
Nifadkar et al. (2012).	11	Feedback Seeking	0.24	0.75	0.67	0.82	0.82	-0.02	0.71
Nifadkar et al. (2012).	11	Interaction Avoidance	0.67	0.38	0.89	0.78	0.78	0.05	0.82

Article	Number of Predictors	Dependent Variable	$\tau_{GD,U}$	$\tau_{GD,C}$	$\tau_{GD,\boldsymbol{m}}$	$\tau_{\boldsymbol{\epsilon},\boldsymbol{r_s^2}}$	$\tau_{\boldsymbol{\epsilon},U}$	$\tau_{\boldsymbol{\epsilon},C}$	$\tau_{\boldsymbol{\epsilon},\boldsymbol{m}}$
Oh & Kilduff (2008).	6	Direct brokerage	0.87	0.60	1.00	0.73	0.73	0.73	0.73
Oh & Kilduff (2008).	7	Indirect brokerage	0.81	0.71	0.71	0.90	0.90	0.52	0.71
Porath & Bateman (2006).	4	Learning goal orientation	1.00	0.00	1.00	0.67	0.67	0.00	1.00
Porath & Bateman (2006).	4	Performance-prove goal orientation	1.00	0.33	1.00	1.00	1.00	0.33	1.00
Porath & Bateman (2006).	4	Performance-avoid goal orientation	1.00	0.67	1.00	1.00	1.00	0.67	1.00

Article	Number of Predictors	Dependent Variable	$\tau_{GD,U}$	$\tau_{GD,C}$	$\tau_{GD,m}$	τ_{ϵ,r_s^2}	$\tau_{\epsilon,U}$	$\tau_{\epsilon,C}$	$\tau_{\epsilon,m}$
Porath & Bateman (2006).	4	Performance	0.67	0.00	1.00	0.67	0.67	0.33	1.00
Porath & Bateman (2006).	5	Performance	0.40	0.00	0.80	0.40	0.40	0.20	0.80
Ragins et al. (2007).	8	degree of disclosure	0.79	0.79	1.00	0.71	0.71	0.57	1.00
Ragins et al. (2007).	8	Fear of disclosure	0.86	0.93	1.00	1.00	1.00	0.79	1.00
Raja et al. (2004).	6	Intentions to quit	0.60	0.60	0.87	0.73	0.73	0.20	0.87
Raja et al. (2004).	6	Affective commitment	0.73	0.47	0.60	0.47	0.47	0.20	0.73

Article	Number of Predictors	Dependent Variable	$\tau_{GD,U}$	$\tau_{GD,C}$	$\tau_{GD,m}$	τ_{ϵ,r_s^2}	$\tau_{\epsilon,U}$	$\tau_{\epsilon,C}$	$\tau_{\epsilon,m}$
Raja et al. (2004).	6	Job satisfaction	0.20	0.87	0.60	1.00	1.00	0.07	0.60
Raja et al. (2004).	5	Intentions to quit	1.00	0.60	1.00	1.00	1.00	0.60	1.00
Raja et al. (2004).	5	Affective commitment	0.60	0.20	0.60	0.60	0.60	-0.20	0.80
Raja et al. (2004).	5	Job satisfaction	0.40	0.60	0.80	0.60	0.60	0.00	0.80
Raja et al. (2004).	6	Intentions to quit	0.20	0.87	0.60	1.00	1.00	0.07	0.60
Raja et al. (2004).	6	Affective commitment	0.60	0.87	0.60	0.73	0.73	0.47	0.73
Raja et al. (2004).	6	Job satisfaction	0.20	0.47	0.73	1.00	1.00	-0.07	0.47

Article	Number of Predictors	Dependent Variable	$\tau_{GD,U}$	$\tau_{GD,C}$	$\tau_{GD,\boldsymbol{m}}$	τ_{ϵ,r_s^2}	$\tau_{\epsilon,U}$	$\tau_{\epsilon,C}$	$\tau_{\epsilon,\boldsymbol{m}}$
Raja et al. (2004).	12	Intentions to quit	0.27	0.73	0.64	0.85	0.85	0.00	0.55
Raja et al. (2004).	12	Affective commitment	0.61	0.82	0.64	0.85	0.85	0.42	0.70
Raja et al. (2004).	12	Job satisfaction	0.30	0.82	0.76	0.94	0.94	0.18	0.79
Raja et al. (2004).	10	Intentions to quit	0.20	0.73	0.60	0.87	0.87	0.02	0.60
Raja et al. (2004).	10	Affective commitment	0.64	0.87	0.64	0.91	0.91	0.60	0.69
Raja et al. (2004).	10	Job satisfaction	0.20	0.82	0.51	0.96	0.96	0.11	0.47
Raub & Liao (2012).	8	Aggregated PCSP	0.43	0.14	0.79	0.79	0.79	0.57	0.79

Article	Number of Predictors	Dependent Variable	$\tau_{GD,U}$	$\tau_{GD,C}$	$\tau_{GD,m}$	τ_{ϵ,r_s^2}	$\tau_{\epsilon,U}$	$\tau_{\epsilon,C}$	$\tau_{\epsilon,m}$
Raub & Liao (2012).	10	Customer service satisfaction	0.73	0.24	0.91	0.38	0.38	-0.02	0.82
Raver et al. (2010).	3	Organizational commitment	1.00	0.33	1.00	1.00	1.00	0.33	1.00
Raver et al. (2010).	3	Job satisfaction	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Raver et al. (2010).	3	Turnover intentions	1.00	-1.00	0.33	0.33	0.33	-1.00	0.33
Raver et al. (2010).	3	Organizational commitment	1.00	0.33	1.00	1.00	1.00	0.33	1.00
Raver et al. (2010).	3	Job satisfaction	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Raver et al. (2010).	3	Turnover intentions	1.00	0.33	1.00	1.00	1.00	0.33	1.00

Article	Number of Predictors	Dependent Variable	$\tau_{GD,U}$	$\tau_{GD,C}$	$\tau_{GD,\boldsymbol{m}}$	$\tau_{\boldsymbol{\epsilon},\boldsymbol{r_s^2}}$	$\tau_{\boldsymbol{\epsilon},U}$	$\tau_{\boldsymbol{\epsilon},C}$	$\tau_{\boldsymbol{\epsilon},\boldsymbol{m}}$
Reynolds (2008).	7	Charitable giving	0.71	0.81	0.90	0.71	0.71	0.52	0.81
Reynolds (2008).	7	Self-reported moral behavior	0.81	0.90	1.00	1.00	1.00	0.71	1.00
Reynolds (2008).	7	Others' moral behavior	0.90	0.90	1.00	0.90	0.90	0.81	1.00
Reynolds (2008).	4	Moral awareness ("present" scenario)	0.67	0.33	1.00	1.00	1.00	0.00	1.00
Reynolds (2008).	4	Moral awareness ("absent" scenario)	1.00	0.33	1.00	0.67	0.67	0.33	1.00
Reynolds et al. (2010).	5	Considerations for shareholders	1.00	0.00	1.00	1.00	1.00	0.00	1.00

Article	Number of Predictors	Dependent Variable	$\tau_{GD,U}$	$\tau_{GD,C}$	$\tau_{GD,\boldsymbol{m}}$	$\tau_{\boldsymbol{\epsilon},\boldsymbol{r_s^2}}$	$\tau_{\epsilon,U}$	$\tau_{\epsilon,C}$	$\tau_{\boldsymbol{\epsilon},\boldsymbol{m}}$
Reynolds et al. (2010).	5	Libertarianism	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Rhee & Fiss (2014).	16	stock market reaction	1.00	0.82	0.98	0.73	0.73	0.82	0.98
Rhee & Fiss (2014).	15	stock market reaction	0.94	0.77	0.98	0.83	0.83	0.79	0.98
Rhee & Fiss (2014).	14	stock market reaction	0.93	0.74	0.98	0.93	0.93	0.76	0.98
Rhee & Fiss (2014).	14	stock market reaction	0.98	0.78	0.98	0.69	0.69	0.80	1.00
Rhee & Fiss (2014).	13	stock market reaction	0.97	0.74	0.97	0.77	0.77	0.77	0.97
Richards et al. (2011).	12	Surface acting	0.82	0.58	0.94	0.67	0.67	0.58	0.91

Article	Number of Predictors	Dependent Variable	$\tau_{GD,U}$	$\tau_{GD,C}$	$\tau_{GD,m}$	τ_{ϵ,r_s^2}	$\tau_{\epsilon,U}$	$\tau_{\epsilon,C}$	$\tau_{\epsilon,m}$
Richards et al. (2011).	12	Instrumental support seeking	0.82	0.55	0.94	0.70	0.70	0.42	0.88
Richards et al. (2011).	12	Emotional support seeking	0.82	0.64	0.94	0.82	0.82	0.45	0.97
Richards et al. (2011).	12	Turnover intention	0.27	0.82	0.48	0.94	0.94	0.15	0.48
Richards et al. (2011).	12	organizational citizenship behaviors directed at the organization	0.73	0.76	0.79	0.76	0.76	0.48	0.76
Salamon & Robinson (2008).	6	Responsibility norms	0.73	1.00	0.87	1.00	1.00	0.73	0.87

Article	Number of Predictors	Dependent Variable	$\tau_{GD,U}$	$\tau_{GD,C}$	$\tau_{GD,\boldsymbol{m}}$	$\tau_{\boldsymbol{\epsilon},\boldsymbol{r_s^2}}$	$\tau_{\boldsymbol{\epsilon},U}$	$\tau_{\boldsymbol{\epsilon},C}$	$\tau_{\boldsymbol{\epsilon},\boldsymbol{m}}$
Salamon & Robinson (2008).	7	Sales	0.71	0.24	1.00	0.62	0.62	0.14	1.00
Salamon & Robinson (2008).	7	Customer service	0.52	0.71	0.81	0.43	0.43	0.24	0.90
Saparito et al. (2004).	14	Likelihood of switching	0.63	0.89	0.78	0.52	0.52	0.65	0.78
Schuelke et al. (2009).	3	Links	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Schuelke et al. (2009).	3	Coherence	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Schuelke et al. (2009).	3	Closeness	0.33	0.33	1.00	1.00	1.00	-0.33	1.00

Article	Number of Predictors	Dependent Variable	$\tau_{GD,U}$	$\tau_{GD,C}$	$\tau_{GD,\boldsymbol{m}}$	$\tau_{\boldsymbol{\epsilon},\boldsymbol{r_s^2}}$	$\tau_{\boldsymbol{\epsilon},U}$	$\tau_{\boldsymbol{\epsilon},C}$	$\tau_{\boldsymbol{\epsilon},\boldsymbol{m}}$
Schuelke et al. (2009).	3	Correlation	1.00	0.33	1.00	1.00	1.00	0.33	1.00
Schuelke et al. (2009).	5	Skill acquisition	0.80	1.00	0.80	1.00	1.00	0.80	0.80
Schuelke et al. (2009).	5	Skill transfer	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Schuelke et al. (2009).	5	Skill acquisition	1.00	1.00	0.80	1.00	1.00	1.00	0.80
Schuelke et al. (2009).	5	Skill transfer	1.00	0.80	1.00	0.80	0.80	0.80	1.00
Schuelke et al. (2009).	5	Skill acquisition	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Schuelke et al. (2009).	5	Skill transfer	0.80	1.00	1.00	1.00	1.00	0.80	1.00

Article	Number of Predictors	Dependent Variable	$\tau_{GD,U}$	$\tau_{GD,C}$	$\tau_{GD,m}$	τ_{ϵ,r_s^2}	$\tau_{\epsilon,U}$	$\tau_{\epsilon,C}$	$\tau_{\epsilon,m}$
Scott & Judge (2009).	5	Organizational citizenship behavior received by employee	0.80	0.80	1.00	1.00	1.00	0.60	1.00
Scott & Judge (2009).	5	Counterproductive work behavior received by employee	0.40	0.80	0.60	1.00	1.00	0.20	0.80
Shaffer et al. (2006).	5	Cultural adjustment	0.60	0.20	0.40	0.60	0.60	-0.20	0.40
Shaffer et al. (2006).	5	Interaction adjustment	0.60	1.00	0.80	1.00	1.00	0.60	0.80
Shaffer et al. (2006).	5	Work adjustment	1.00	0.40	1.00	0.80	0.80	0.40	1.00

Article	Number of Predictors	Dependent Variable	$\tau_{GD,U}$	$\tau_{GD,C}$	$\tau_{GD,\boldsymbol{m}}$	τ_{ϵ,r_s^2}	$\tau_{\epsilon,U}$	$\tau_{\epsilon,C}$	$\tau_{\epsilon,\boldsymbol{m}}$
Shaffer et al. (2006).	5	Withdrawal cognitions	0.80	0.80	1.00	0.80	0.80	0.60	1.00
Shaffer et al. (2006).	5	Contextual performance	0.20	0.60	1.00	0.80	0.80	-0.20	1.00
Shaffer et al. (2006).	5	Task performance	0.60	1.00	0.60	0.60	0.60	0.60	0.40
Shaffer et al. (2006).	4	Cultural adjustment	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Shaffer et al. (2006).	4	Interaction adjustment	0.67	1.00	0.67	1.00	1.00	0.67	0.67
Shaffer et al. (2006).	4	Work adjustment	0.33	0.33	0.67	0.67	0.67	-0.33	0.67
Shaffer et al. (2006).	4	Withdrawal cognitions	1.00	0.00	1.00	0.33	0.33	0.00	1.00

Article	Number of Predictors	Dependent Variable	$\tau_{GD,U}$	$\tau_{GD,C}$	$\tau_{GD,\boldsymbol{m}}$	$\tau_{\boldsymbol{\epsilon},\boldsymbol{r_s^2}}$	$\tau_{\boldsymbol{\epsilon},U}$	$\tau_{\boldsymbol{\epsilon},C}$	$\tau_{\boldsymbol{\epsilon},\boldsymbol{m}}$
Shaffer et al. (2006).	4	Contextual performance	0.67	0.67	1.00	1.00	1.00	0.33	1.00
Shaffer et al. (2006).	4	Task performance	0.67	1.00	1.00	1.00	1.00	0.67	1.00
Shaffer et al. (2006).	4	Cultural adjustment	0.67	1.00	1.00	1.00	1.00	0.67	1.00
Shaffer et al. (2006).	4	Interaction adjustment	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Shaffer et al. (2006).	4	Work adjustment	1.00	0.67	1.00	1.00	1.00	0.67	1.00
Shaffer et al. (2006).	4	Withdrawal cognitions	1.00	0.67	1.00	1.00	1.00	0.67	1.00
Shaffer et al. (2006).	4	Contextual performance	1.00	0.33	1.00	1.00	1.00	0.33	1.00

Article	Number of Predictors	Dependent Variable	$\tau_{GD,U}$	$\tau_{GD,C}$	$\tau_{GD,m}$	τ_{ϵ,r_s^2}	$\tau_{\epsilon,U}$	$\tau_{\epsilon,C}$	$\tau_{\epsilon,m}$
Shaffer et al. (2006).	4	Task performance	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Shapiro et al. (2011).	19	Employee's turnover intentions	0.71	0.32	0.84	0.61	0.61	0.43	0.86
Shapiro et al. (2011).	19	Employee's psychological withdrawal	0.75	0.63	0.91	0.68	0.68	0.43	0.88
Shapiro et al. (2011).	16	Leader–member exchange	0.70	0.60	0.95	0.72	0.72	0.43	0.97
Simons et al. (2007).	7	Trust in manager	0.43	0.62	0.62	0.62	0.62	0.24	0.62
Simons et al. (2007).	7	Interpersonal justice	0.81	1.00	0.90	0.81	0.81	0.81	0.90

Article	Number of Predictors	Dependent Variable	$\tau_{GD,U}$	$\tau_{GD,C}$	$\tau_{GD,\boldsymbol{m}}$	$\tau_{\boldsymbol{\epsilon},\boldsymbol{r_s^2}}$	$\tau_{\boldsymbol{\epsilon},U}$	$\tau_{\boldsymbol{\epsilon},C}$	$\tau_{\boldsymbol{\epsilon},\boldsymbol{m}}$
Simons et al. (2007).	7	Satisfaction	0.71	0.90	0.81	0.81	0.81	0.62	0.81
Simons et al. (2007).	7	Commitment	0.81	0.71	1.00	1.00	1.00	0.52	1.00
Simons et al. (2007).	7	Intent to stay	0.90	0.62	0.90	0.90	0.90	0.71	0.90
Slaughter et al. (2014).	14	initial belief confidence	0.63	0.76	0.56	0.82	0.82	0.38	0.63
Strauss et al. (2012).	8	Proactive career behavior	0.93	0.86	0.93	1.00	1.00	0.79	0.93
Strauss et al. (2012).	5	Proactive career behavior	0.60	1.00	1.00	1.00	1.00	0.60	1.00
Strauss et al. (2012).	6	Proactive career behavior Time 2	0.73	1.00	0.87	1.00	1.00	0.73	1.00

Article	Number of Predictors	Dependent Variable	$\tau_{GD,U}$	$\tau_{GD,C}$	$\tau_{GD,m}$	τ_{ϵ,r_s^2}	$\tau_{\epsilon,U}$	$\tau_{\epsilon,C}$	$\tau_{\epsilon,m}$
Summers et al. (2012).	5	Task performance, time 3	1.00	0.80	1.00	1.00	1.00	0.80	1.00
Takeuchi et al. (2007).	13	Collective human capital	0.74	0.67	0.74	0.62	0.62	0.62	0.74
Takeuchi et al. (2007).	13	Degree of establishment social exchange	0.56	0.77	0.82	0.72	0.72	0.38	0.85
Takeuchi et al. (2007).	13	Collective human capital	0.62	0.54	0.64	0.56	0.56	0.51	0.59
Takeuchi et al. (2007).	13	Degree of establishment social exchange	0.90	0.31	0.82	0.77	0.77	0.26	0.77

Article	Number of Predictors	Dependent Variable	$\tau_{GD,U}$	$\tau_{GD,C}$	$\tau_{GD,m}$	τ_{ϵ,r_s^2}	$\tau_{\epsilon,U}$	$\tau_{\epsilon,C}$	$\tau_{\epsilon,m}$
Takeuchi et al. (2007).	15	Relative establishment performance	0.56	0.60	0.83	0.71	0.71	0.47	0.87
Takeuchi et al. (2007).	15	Relative establishment performance	0.35	0.31	0.68	0.75	0.75	0.05	0.66
Tay et al. (2006).	11	Interview success	0.53	0.75	0.60	0.56	0.56	0.42	0.49
Tay et al. (2006).	10	Initial Interview Self Elficacy	0.42	0.47	0.38	0.51	0.51	0.16	0.42
Trevor & Nyberg (2008).	17	turnover	0.57	0.91	0.74	0.68	0.68	0.51	0.72
Trevor & Nyberg (2008).	16	turnover	0.62	0.83	0.78	0.73	0.73	0.45	0.78

Article	Number of Predictors	Dependent Variable	$\tau_{GD,U}$	$\tau_{GD,C}$	$\tau_{GD,m}$	τ_{ϵ,r_s^2}	$\tau_{\epsilon,U}$	$\tau_{\epsilon,C}$	$\tau_{\epsilon,m}$
Trevor & Nyberg (2008).	16	commitment	0.57	0.53	0.85	0.77	0.77	0.43	0.87
van Hooft & Noordzij (2009).	8	Job search behavior	0.29	0.86	0.79	0.86	0.86	0.14	0.79
van Hooft & Noordzij (2009).	7	Job search intention	0.90	0.81	1.00	0.90	0.90	0.71	1.00
Van Hoye & Lievens (2009).	4	Positive word-of-mouth	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Van Hoye & Lievens (2009).	4	Negative word-of-mouth	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Van Hoye & Lievens (2009).	7	Organizational attractiveness	0.62	0.71	0.71	0.81	0.81	0.33	0.71
Van Iddekinge et al. (2011).	6	Technical knowledge	0.73	0.60	0.60	0.73	0.73	0.60	0.87

Article	Number of Predictors	Dependent Variable	$\tau_{GD,U}$	$\tau_{GD,C}$	$\tau_{GD,\boldsymbol{m}}$	$\tau_{\boldsymbol{\epsilon},\boldsymbol{r_s^2}}$	$\tau_{\boldsymbol{\epsilon},U}$	$\tau_{\boldsymbol{\epsilon},C}$	$\tau_{\boldsymbol{\epsilon},\boldsymbol{m}}$
Van Iddekinge et al. (2011).	6	Interpersonal knowledge	0.87	0.73	0.73	0.60	0.60	0.60	1.00
Van Iddekinge et al. (2011).	6	Task proficiency	1.00	0.73	0.60	0.60	0.60	0.73	0.73
Van Iddekinge et al. (2011).	6	Effort	0.87	0.87	0.87	0.87	0.87	0.73	0.60
Van Iddekinge et al. (2011).	6	Continuance intentions	0.60	0.33	0.87	1.00	1.00	-0.07	0.87
Wallace et al. (2006).	4	Safety climate	1.00	0.67	1.00	1.00	1.00	0.67	1.00
Wallace et al. (2006).	5	Accidents	0.60	0.80	1.00	0.80	0.80	0.40	1.00
Wallace et al. (2006).	4	Safety climate	1.00	0.67	1.00	1.00	1.00	0.67	1.00

Article	Number of Predictors	Dependent Variable	$\tau_{GD,U}$	$\tau_{GD,C}$	$\tau_{GD,\boldsymbol{m}}$	τ_{ϵ,r_s^2}	$\tau_{\epsilon,U}$	$\tau_{\epsilon,C}$	$\tau_{\epsilon,\boldsymbol{m}}$
Wallace et al. (2006).	5	Accidents	0.60	1.00	1.00	0.80	0.80	0.60	1.00
Walters et al. (2010).	16	holding period returns	0.80	0.67	0.80	0.77	0.77	0.53	0.80
Walters et al. (2010).	17	holding period returns	0.81	0.75	0.84	0.78	0.78	0.56	0.81
Zhang & Peterson (2011).	7	Team performance	0.62	0.81	0.81	1.00	1.00	0.43	0.81
Zhang & Peterson (2011).	6	Advice network density	0.87	0.60	0.87	1.00	1.00	0.47	0.87

Article	Number of Predictors	Dependent Variable	$\tau_{r_s^2,U}$	$\tau_{r_s^2,C}$	$\tau_{r_s^2,m}$	$\tau_{U,C}$	$\tau_{U,m}$	$\tau_{C,m}$
Agle et al. (2006).	3	CEO charisma	0.33	0.33	0.33	-0.33	1.00	-0.33
Agle et al. (2006).	3	CEO charisma	1.00	1.00	1.00	1.00	1.00	1.00
Agle et al. (2006).	3	CEO charisma	1.00	0.33	1.00	0.33	1.00	0.33
Agle et al. (2006).	3	CEO charisma	1.00	1.00	1.00	1.00	1.00	1.00
Agle et al. (2006).	3	CEO charisma	1.00	1.00	1.00	1.00	1.00	1.00
Agle et al. (2006).	3	CEO charisma	1.00	1.00	1.00	1.00	1.00	1.00
Anderson et al. (2008).	12	Influence	0.48	0.85	0.79	0.39	0.70	0.64

Article	Number of Predictors	Dependent Variable	$\tau_{r_s^2,U}$	$\tau_{r_s^2,C}$	$\tau_{r_s^2,m}$	$\tau_{U,C}$	$\tau_{U,m}$	$\tau_{C,m}$
Anderson et al. (2008).	12	Influence	0.45	0.30	0.67	0.67	0.73	0.52
Aryee et al. (2012).	5	Branch market performance	0.20	0.20	0.80	0.20	0.40	0.40
Austin (2003).	5	Goal attainment	0.60	1.00	0.60	0.60	1.00	0.60
Austin (2003).	5	Ext evaluation	0.80	0.80	1.00	0.60	0.80	0.80
Austin (2003).	5	Internal evaluation	0.20	1.00	0.60	0.20	0.60	0.60
Balkundi et al. (2011).	8	Team performance	0.71	0.57	0.86	0.57	0.86	0.71
Balkundi et al. (2011).	7	Leader charisma	0.33	0.43	0.81	0.52	0.52	0.43
Balkundi et al. (2011).	7	Leader centrality	0.52	0.43	0.81	-0.05	0.71	0.24

Article	Number of Predictors	Dependent Variable	$\tau_{r_s^2,U}$	$\tau_{r_s^2,C}$	$\tau_{r_s^2,m}$	$\tau_{U,C}$	$\tau_{U,m}$	$\tau_{C,m}$
Balkundi et al. (2011).	6	Leader charisma (T2)	0.33	0.07	0.60	0.20	0.47	-0.07
Balkundi et al. (2011).	6	Leader centrality (T2)	0.20	0.47	0.87	0.20	0.33	0.33
Balkundi et al. (2011).	8	Team performance (T3)	0.36	0.36	0.71	0.14	0.64	0.07
Bansal & Clelland (2004).	11	Unsystematic risk	0.71	0.67	0.93	0.38	0.78	0.60
Barnes et al.(2008).	3	Team performance	1.00	1.00	1.00	1.00	1.00	1.00
Barnett & King (2008).	5	cumulative abnormal return	1.00	0.60	0.80	0.60	0.80	0.40
Barnett & King (2008).	3	cumulative abnormal return	1.00	0.33	1.00	0.33	1.00	0.33

Article	Number of Predictors	Dependent Variable	$\tau_{r_s^2,U}$	$\tau_{r_s^2,C}$	$\tau_{r_s^2,m}$	$\tau_{U,C}$	$\tau_{U,m}$	$\tau_{C,m}$
Barrick et al. (2010).	4	Interview score	0.33	1.00	0.67	0.33	0.67	0.67
Barrick et al. (2010).	4	Interview score (structured only; in Interview 3)	1.00	0.67	1.00	0.67	1.00	0.67
Barrick et al. (2010).	4	Second interview	0.33	0.33	0.33	-0.33	1.00	-0.33
Bell et al. (2006).	5	Procedural justice expectations (1)	1.00	1.00	1.00	1.00	1.00	1.00
Bell et al. (2006).	5	Distributive justice expectations (1)	0.80	0.00	0.80	0.20	1.00	0.20

Article	Number of Predictors	Dependent Variable	$\tau_{r_s^2,U}$	$\tau_{r_s^2,C}$	$\tau_{r_s^2,m}$	$\tau_{U,C}$	$\tau_{U,m}$	$\tau_{C,m}$
Bell et al. (2006).	5	Interpersonal justice expectations (1)	0.80	0.60	0.80	0.80	1.00	0.80
Bell et al. (2006).	5	Informational justice expectations (1)	0.40	0.40	0.40	1.00	1.00	1.00
Bell et al. (2006).	9	Test-taking efficacy (1)	0.72	0.89	1.00	0.72	0.72	0.89
Bell et al. (2006).	9	Test-taking motivation (1)	0.67	0.67	0.89	0.56	0.78	0.67
Bell et al. (2006).	9	Intention to accept job (1)	0.61	0.89	0.83	0.72	0.78	0.83
Bell et al. (2006).	9	Intention to recommend job (1)	0.83	0.94	0.83	0.78	1.00	0.78

Article	Number of Predictors	Dependent Variable	$\tau_{r_s^2,U}$	$\tau_{r_s^2,C}$	$\tau_{r_s^2,m}$	$\tau_{U,C}$	$\tau_{U,m}$	$\tau_{C,m}$
Bell et al. (2006).	10	Procedural justice perceptions (2)	0.24	0.56	0.69	0.07	0.47	0.33
Bell et al. (2006).	10	Distributive justice perceptions (2)	0.42	0.64	0.69	0.42	0.64	0.51
Bell et al. (2006).	10	Interpersonal justice perceptions (2)	0.42	0.78	0.69	0.47	0.73	0.64
Bell et al. (2006).	10	Informational justice perceptions (2)	0.56	0.73	0.91	0.47	0.64	0.73
Bernerth et al. (2012).	5	FICO	0.80	0.80	0.80	0.60	1.00	0.60

Article	Number of Predictors	Dependent Variable	$\tau_{r_s^2,U}$	$\tau_{r_s^2,C}$	$\tau_{r_s^2,m}$	$\tau_{U,C}$	$\tau_{U,m}$	$\tau_{C,m}$
Bordia et al. (2008).	4	Minor offenses (Time 2)	0.33	0.33	1.00	1.00	0.33	0.33
Bordia et al. (2008).	4	Major offenses (Time 2)	0.67	1.00	1.00	0.67	0.67	1.00
Brett & Stroh (2003).	20	Work hours	0.35	0.62	0.65	0.26	0.69	0.46
Brett & Stroh (2003).	20	Work hours	0.36	0.81	0.62	0.19	0.63	0.43
Brown & Treviño (2009).	6	Self-enhancement (E)	0.60	-0.33	1.00	0.07	0.60	-0.33
Brown & Treviño (2009).	6	Openness to change (E)	0.47	0.07	0.87	0.07	0.60	0.20
Brown & Treviño (2009).	6	Conservation (E)	0.33	0.60	0.47	0.20	0.60	0.60

Article	Number of Predictors	Dependent Variable	$\tau_{r_s^2,U}$	$\tau_{r_s^2,C}$	$\tau_{r_s^2,m}$	$\tau_{U,C}$	$\tau_{U,m}$	$\tau_{C,m}$
Brown & Treviño (2009).	5	Self-enhancement (L)	0.60	0.60	0.60	0.20	1.00	0.20
Brown & Treviño (2009).	5	Openness to change (L)	0.80	0.80	0.80	1.00	1.00	1.00
Brown & Treviño (2009).	5	Conservation (L)	0.80	0.80	1.00	1.00	0.80	0.80
Brown & Treviño (2006).	4	Organizational deviance	1.00	1.00	1.00	1.00	1.00	1.00
Brown & Treviño (2006).	4	Values congruence	0.67	1.00	0.67	0.67	1.00	0.67
Brown & Treviño (2006).	4	Interpersonal deviance	1.00	0.67	1.00	0.67	1.00	0.67
Brown & Treviño (2006).	5	Organizational deviance	1.00	1.00	1.00	1.00	1.00	1.00

Article	Number of Predictors	Dependent Variable	$\tau_{r_s^2,U}$	$\tau_{r_s^2,C}$	$\tau_{r_s^2,m}$	$\tau_{U,C}$	$\tau_{U,m}$	$\tau_{C,m}$
Carton et al.(2014).	20	heart attack readmission prevention	0.11	0.47	0.74	0.27	0.35	0.29
Carton et al.(2014).	18	heart attack readmission prevention	0.11	0.50	0.63	0.40	0.42	0.24
Charles et al.(2013).	7	Wave 2 general affective distress	0.71	0.90	0.81	0.62	0.90	0.71
Charles et al.(2013).	6	Wave 2 general affective distress	0.73	0.87	0.87	0.60	0.87	0.73
Charles et al.(2013).	6	Wave 2 general affective distress	0.73	0.60	0.73	0.33	1.00	0.33
Chen et al.(2011).	4	Psychological empowerment	0.67	-0.33	1.00	0.00	0.67	-0.33

Article	Number of Predictors	Dependent Variable	$\tau_{r_s^2,U}$	$\tau_{r_s^2,C}$	$\tau_{r_s^2,m}$	$\tau_{U,C}$	$\tau_{U,m}$	$\tau_{C,m}$
Chen et al.(2011).	4	Affective commitment	1.00	0.67	1.00	0.67	1.00	0.67
Chen et al.(2005).	3	Transition processes	0.33	1.00	0.33	0.33	1.00	0.33
Chen et al.(2005).	4	Action processes	1.00	1.00	1.00	1.00	1.00	1.00
Chen et al.(2005).	5	Team adaptive performance	0.40	0.60	0.60	0.00	0.80	0.20
Christmann (2004).	8	Level of internal global environmental performance standards	0.57	0.57	0.64	0.14	0.93	0.21

Article	Number of Predictors	Dependent Variable	$\tau_{r_s^2,U}$	$\tau_{r_s^2,C}$	$\tau_{r_s^2,m}$	$\tau_{U,C}$	$\tau_{U,m}$	$\tau_{C,m}$
Christmann (2004).	8	Global operational environmental policy standardization	0.57	0.79	0.86	0.36	0.71	0.64
Christmann (2004).	8	Global environmental communication standardization	0.43	0.21	0.71	0.21	0.71	0.21
Conlon et al. (2006).	8	Logged Citations	0.43	0.07	0.64	0.36	0.79	0.29
Conlon et al. (2006).	10	Logged Citations	0.11	0.02	0.47	0.56	0.64	0.38
Courtright et al. (2014).	4	Engagement	1.00	0.67	1.00	0.67	1.00	0.67

Article	Number of Predictors	Dependent Variable	$\tau_{r_s^2,U}$	$\tau_{r_s^2,C}$	$\tau_{r_s^2,m}$	$\tau_{U,C}$	$\tau_{U,m}$	$\tau_{C,m}$
Courtright et al. (2014).	5	Emotional exhaustion	0.60	1.00	1.00	0.60	0.60	1.00
Courtright et al. (2014).	6	Transformational leadership	0.60	0.33	0.87	-0.07	0.47	0.47
Courtright et al. (2014).	6	Laissez faire leadership	0.20	-0.33	0.73	0.47	0.47	-0.07
Cross & Cummings (2004).	11	Performance	0.35	0.56	0.60	0.05	0.75	0.24
Cross & Cummings (2004).	11	Performance	0.45	0.78	0.78	0.31	0.67	0.64
Curhan, Elfenbein & Kilduff (2009).	11	Compensation satisfaction	0.49	0.42	0.78	0.20	0.71	0.27

Article	Number of Predictors	Dependent Variable	$\tau_{r_s^2,U}$	$\tau_{r_s^2,C}$	$\tau_{r_s^2,m}$	$\tau_{U,C}$	$\tau_{U,m}$	$\tau_{C,m}$
Curhan, Elfenbein & Kilduff (2009).	11	Job satisfaction	0.45	0.13	0.60	0.31	0.85	0.31
Curhan, Elfenbein & Kilduff (2009).	11	Turnover intention	0.60	0.53	0.78	0.35	0.75	0.45
Dabos & Rousseau (2004).	3	Scientist Transactional (S)	1.00	1.00	1.00	1.00	1.00	1.00
Dabos & Rousseau (2004).	3	Scientist Relational (S)	1.00	0.33	1.00	0.33	1.00	0.33
Dabos & Rousseau (2004).	3	Scientist Balanced (S)	1.00	1.00	1.00	1.00	1.00	1.00

Article	Number of Predictors	Dependent Variable	$\tau_{r_s^2,U}$	$\tau_{r_s^2,C}$	$\tau_{r_s^2,m}$	$\tau_{U,C}$	$\tau_{U,m}$	$\tau_{C,m}$
Dabos & Rousseau (2004).	3	Director Transactional (S)	1.00	1.00	1.00	1.00	1.00	1.00
Dabos & Rousseau (2004).	3	Director Relational (S)	1.00	1.00	1.00	1.00	1.00	1.00
Dabos & Rousseau (2004).	3	Director Balanced (S)	1.00	0.33	1.00	0.33	1.00	0.33
Davidson et al. (2004).	7	Discretionary current accruals	0.62	0.33	0.62	0.52	1.00	0.52
Davidson et al. (2004).	6	Discretionary current accruals	0.47	0.07	0.47	0.07	1.00	0.07
Davidson et al. (2004).	5	Discretionary current accruals	0.60	0.20	0.60	0.60	1.00	0.60

Article	Number of Predictors	Dependent Variable	$\tau_{r_s^2,U}$	$\tau_{r_s^2,C}$	$\tau_{r_s^2,m}$	$\tau_{U,C}$	$\tau_{U,m}$	$\tau_{C,m}$
de Jong et al. (2014).	4	team performance	0.67	0.67	1.00	1.00	0.67	0.67
de Vries et al.(2014).	4	interteam coordination	0.67	0.00	1.00	-0.33	0.67	0.00
de Vries et al.(2014).	3	cognitive complexity	1.00	1.00	1.00	1.00	1.00	1.00
de Vries et al.(2014).	5	interteam coordination	0.80	0.20	1.00	0.00	0.80	0.20
DeChurch & Marks (2006).	3	Interteam coordination (explicit)	0.33	0.33	1.00	-0.33	0.33	0.33
DeChurch & Marks (2006).	3	Interteam coordination (implicit)	-1.00	1.00	-0.33	-1.00	0.33	-0.33

Article	Number of Predictors	Dependent Variable	$\tau_{r_s^2,U}$	$\tau_{r_s^2,C}$	$\tau_{r_s^2,m}$	$\tau_{U,C}$	$\tau_{U,m}$	$\tau_{C,m}$
DeChurch & Marks (2006).	3	Interteam coordination (explicit)	1.00	1.00	1.00	1.00	1.00	1.00
DeChurch & Marks (2006).	3	Interteam coordination (implicit)	0.33	1.00	0.33	0.33	1.00	0.33
DeChurch & Marks (2006).	4	MTS performance	0.00	0.67	1.00	-0.33	0.00	0.67
DeChurch & Marks (2006).	4	MTS performance	0.67	0.67	1.00	0.33	0.67	0.67
DeChurch & Marks (2006).	4	MTS performance	0.67	1.00	0.67	0.67	1.00	0.67
DeChurch & Marks (2006).	4	MTS performance	0.67	0.67	1.00	0.33	0.67	0.67

Article	Number of Predictors	Dependent Variable	$\tau_{r_s^2,U}$	$\tau_{r_s^2,C}$	$\tau_{r_s^2,m}$	$\tau_{U,C}$	$\tau_{U,m}$	$\tau_{C,m}$
DeChurch & Marks (2006).	5	MTS performance	0.80	0.40	0.80	0.20	1.00	0.20
DeChurch & Marks (2006).	5	MTS performance	0.80	0.60	1.00	0.40	0.80	0.60
DeChurch et al. (2013).	5	Performance	0.80	0.80	1.00	0.60	0.80	0.80
DeChurch et al. (2013).	5	Affective outcomes	0.80	0.80	0.80	0.60	1.00	0.60
DeChurch et al. (2013).	3	Performance	0.33	1.00	1.00	0.33	0.33	1.00
DeChurch et al. (2013).	3	Affective outcomes	1.00	1.00	1.00	1.00	1.00	1.00
DeRue & Morgeson (2007).	3	Person–role fit (Time 5)	1.00	1.00	1.00	1.00	1.00	1.00

Article	Number of Predictors	Dependent Variable	$\tau_{r_s^2,U}$	$\tau_{r_s^2,C}$	$\tau_{r_s^2,m}$	$\tau_{U,C}$	$\tau_{U,m}$	$\tau_{C,m}$
DeRue et al. (2008).	6	team performance	0.47	0.20	0.60	0.20	0.87	0.07
Detert et al. (2008).	10	Moral disengagement	0.64	0.33	0.78	0.24	0.87	0.20
Detert et al. (2008).	11	Unethical decisions	0.45	0.78	0.71	0.45	0.75	0.56
Detert et al. (2007).	15	Operating profit	0.35	0.94	0.66	0.30	0.70	0.60
Detert et al. (2007).	15	Customer Satisfaction	0.43	0.64	0.71	0.60	0.64	0.62
Detert et al. (2007).	14	Food loss	0.60	0.63	0.91	0.41	0.69	0.58
Dierdorff & Morgeson (2007).	6	Task requirements	0.60	0.20	0.87	0.60	0.73	0.33

Article	Number of Predictors	Dependent Variable	$\tau_{r_s^2,U}$	$\tau_{r_s^2,C}$	$\tau_{r_s^2,m}$	$\tau_{U,C}$	$\tau_{U,m}$	$\tau_{C,m}$
Dierdorff & Morgeson (2007).	6	Responsibility requirements	0.33	0.87	0.60	0.20	0.73	0.47
Dierdorff & Morgeson (2007).	6	Trait requirements	0.47	0.60	0.73	0.07	0.73	0.33
Drescher et al. (2014).	6	trusting behavior change	0.33	1.00	0.73	0.33	0.60	0.73
Drescher et al. (2014).	6	trusting behavior time 3	0.60	0.87	0.60	0.47	1.00	0.47
Duffy et al. (2012).	8	Social undermining, time 2	0.64	0.14	0.71	0.07	0.93	0.14

Article	Number of Predictors	Dependent Variable	$\tau_{r_s^2,U}$	$\tau_{r_s^2,C}$	$\tau_{r_s^2,m}$	$\tau_{U,C}$	$\tau_{U,m}$	$\tau_{C,m}$
Eby et al. (2008).	9	Protege intentions to leave the relationship	0.33	0.67	0.67	0.00	0.67	0.33
Eby et al. (2008).	9	Protege receipt of career-related mentoring	0.33	0.94	0.56	0.28	0.67	0.50
Eby et al. (2008).	9	Protege receipt of psychosocial mentoring	0.22	0.94	0.67	0.28	0.56	0.61
Eby et al. (2008).	9	Mentor intentions to leave the relationship	0.11	0.94	0.50	0.17	0.61	0.56

Article	Number of Predictors	Dependent Variable	$\tau_{r_s^2,U}$	$\tau_{r_s^2,C}$	$\tau_{r_s^2,m}$	$\tau_{U,C}$	$\tau_{U,m}$	$\tau_{C,m}$
Eby et al. (2008).	9	Mentor burnout	0.00	0.39	0.39	0.06	0.61	0.11
Edwards et al. (2006).	3	Average team performanc	0.33	0.33	0.33	-0.33	1.00	-0.33
Edwards et al. (2006).	3	Average team performanc	1.00	0.33	0.33	0.33	0.33	1.00
Firth et al. (2014).	8	initial work adjustment	0.57	0.86	0.93	0.57	0.64	0.79
Firth et al. (2014).	9	work adjustment change	0.44	0.56	0.94	0.56	0.50	0.61
Firth et al. (2014).	10	premature return intention	0.33	0.24	0.60	0.56	0.64	0.47
Firth et al. (2014).	10	job satisfaction	0.42	0.69	0.60	0.64	0.82	0.73

Article	Number of Predictors	Dependent Variable	$\tau_{r_s^2,U}$	$\tau_{r_s^2,C}$	$\tau_{r_s^2,m}$	$\tau_{U,C}$	$\tau_{U,m}$	$\tau_{C,m}$
Fisher (2014).	5	Coordination	0.00	0.40	1.00	0.60	0.00	0.40
Fisher (2014).	5	Interpersonal processes	0.20	0.80	0.20	0.00	1.00	0.00
Fisher (2014).	5	Coordination	0.40	0.40	1.00	1.00	0.40	0.40
Fisher (2014).	5	Interpersonal processes	0.40	0.60	0.40	0.00	1.00	0.00
Fisher et al. (2012).	7	TMM similarity	0.71	0.52	0.81	0.81	0.90	0.71
Fisher et al. (2012).	4	Implicit coordination	0.33	0.33	0.67	1.00	0.67	0.67
Fisher et al. (2012).	4	Team performance	1.00	-0.33	0.33	-0.33	0.33	0.33
Flynn & Brockner (2003).	6	Commitment	0.60	0.87	0.60	0.47	1.00	0.47

Article	Number of Predictors	Dependent Variable	$\tau_{r_s^2,U}$	$\tau_{r_s^2,C}$	$\tau_{r_s^2,m}$	$\tau_{U,C}$	$\tau_{U,m}$	$\tau_{C,m}$
Flynn & Brockner (2003).	6	Commitment	0.60	0.87	0.73	0.47	0.87	0.60
Flynn & Brockner (2003).	6	Commitment	0.47	0.60	0.60	0.07	0.87	0.20
Flynn & Brockner (2003).	6	Commitment	0.47	0.87	0.60	0.33	0.87	0.47
Flynn & Schaumberg (2012).	3	Affective commitment	1.00	0.33	1.00	0.33	1.00	0.33
Flynn & Schaumberg (2012).	4	Affective commitment	0.67	0.67	1.00	1.00	0.67	0.67

Article	Number of Predictors	Dependent Variable	$\tau_{r_s^2,U}$	$\tau_{r_s^2,C}$	$\tau_{r_s^2,m}$	$\tau_{U,C}$	$\tau_{U,m}$	$\tau_{C,m}$
Flynn & Schaumberg (2012).	4	Work effort	1.00	0.67	1.00	0.67	1.00	0.67
Flynn & Schaumberg (2012).	8	Affective commitment	0.43	0.00	0.71	-0.29	0.71	-0.29
Flynn & Schaumberg (2012).	8	Work effort	0.57	0.57	1.00	0.29	0.57	0.57
Fritz & Sonnentag (2006).	12	health complaints t3	0.27	0.82	0.55	0.27	0.73	0.48
Fritz & Sonnentag (2006).	12	health complaints t4	0.09	0.85	0.55	0.18	0.48	0.52

Article	Number of Predictors	Dependent Variable	$\tau_{r_s^2,U}$	$\tau_{r_s^2,C}$	$\tau_{r_s^2,m}$	$\tau_{U,C}$	$\tau_{U,m}$	$\tau_{C,m}$
Fritz & Sonnentag (2006).	12	Exhaustion T3	0.45	0.91	0.82	0.42	0.64	0.73
Fritz & Sonnentag (2006).	12	Exhaustion T4	0.58	0.85	0.76	0.61	0.82	0.67
Fritz & Sonnentag (2006).	12	Disengagement T3	0.30	0.94	0.76	0.24	0.55	0.70
Fritz & Sonnentag (2006).	12	Disengagement T4	0.36	0.85	0.76	0.39	0.61	0.67
Fritz & Sonnentag (2006).	12	Task performance T3	0.30	0.21	0.76	0.24	0.55	0.27

Article	Number of Predictors	Dependent Variable	$\tau_{r_s^2,U}$	$\tau_{r_s^2,C}$	$\tau_{r_s^2,m}$	$\tau_{U,C}$	$\tau_{U,m}$	$\tau_{C,m}$
Fritz & Sonnentag (2006).	12	Task performance T4	0.30	0.85	0.48	0.15	0.76	0.33
Fritz & Sonnentag (2006).	12	Effort expenditure T3	0.64	0.55	0.88	0.42	0.76	0.55
Fritz & Sonnentag (2006).	12	Effort expenditure T4	0.21	0.42	0.64	0.36	0.58	0.48
Fritz et al. (2010).	9	Exhaustion	0.72	0.72	1.00	0.67	0.72	0.72
Fritz et al. (2010).	9	Life satisfaction	0.56	0.89	0.89	0.56	0.67	0.78

Article	Number of Predictors	Dependent Variable	$\tau_{r_s^2,U}$	$\tau_{r_s^2,C}$	$\tau_{r_s^2,m}$	$\tau_{U,C}$	$\tau_{U,m}$	$\tau_{C,m}$
Gardner et al. (2012).	9	Knowledge integration capability	0.67	0.72	0.83	0.61	0.83	0.67
Glebbeek & Bax (2004).	4	Net Result, 1995–98	0.33	0.00	0.67	0.67	0.67	0.33
Glebbeek & Bax (2004).	3	Net Result, 1995–98	1.00	0.33	1.00	0.33	1.00	0.33
Glebbeek & Bax (2004).	4	Net Result, 1997–98	1.00	0.67	1.00	0.67	1.00	0.67
Glebbeek & Bax (2004).	3	Net Result, 1997–98	1.00	-0.33	1.00	-0.33	1.00	-0.33
Glebbeek & Bax (2004).	5	Net Result, 1996–98	0.80	0.40	1.00	0.60	0.80	0.40
Glebbeek & Bax (2004).	4	Net Result, 1996–98	1.00	1.00	1.00	1.00	1.00	1.00

Article	Number of Predictors	Dependent Variable	$\tau_{r_s^2,U}$	$\tau_{r_s^2,C}$	$\tau_{r_s^2,m}$	$\tau_{U,C}$	$\tau_{U,m}$	$\tau_{C,m}$
Glebbeek & Bax (2004).	5	Net Result, 1997–98	0.80	0.20	1.00	0.40	0.80	0.20
Glebbeek & Bax (2004).	4	Net Result, 1997–98	1.00	1.00	1.00	1.00	1.00	1.00
Gong et al. (2009).	14	Firm performance	0.32	0.49	0.76	0.25	0.56	0.34
Gong et al. (2009).	12	Affective commitment	0.67	0.64	0.82	0.30	0.85	0.45
Gong et al. (2009).	12	Continuance commitment	0.30	0.64	0.70	0.42	0.61	0.52
Gonzalez-Mulé et al. (2014).	5	cooperative group norms	0.60	0.80	0.80	0.40	0.80	0.60
Gonzalez-Mulé et al. (2014).	6	cwb	0.47	-0.07	1.00	0.47	0.47	-0.07

Article	Number of Predictors	Dependent Variable	$\tau_{r_s^2,U}$	$\tau_{r_s^2,C}$	$\tau_{r_s^2,m}$	$\tau_{U,C}$	$\tau_{U,m}$	$\tau_{C,m}$
Gonzalez-Mulé et al. (2014).	6	ocb	0.87	-0.20	1.00	-0.33	0.87	-0.20
Gonzalez-Mulé et al. (2014).	6	task performance	0.47	0.47	0.60	0.20	0.87	0.07
Gonzalez-Mulé et al. (2014).	6	job performance	1.00	0.47	1.00	0.47	1.00	0.47
Gupta et al. (2013).	6	Sales performance	0.87	0.47	1.00	0.60	0.87	0.47
Gupta et al. (2013).	6	Performance appraisal	0.87	0.20	1.00	0.33	0.87	0.20
Gupta et al. (2013).	7	Sales performance	0.81	0.43	0.90	0.24	0.90	0.33
Gupta et al. (2013).	7	Performance appraisal	0.43	0.52	0.90	0.33	0.52	0.43

Article	Number of Predictors	Dependent Variable	$\tau_{r_s^2,U}$	$\tau_{r_s^2,C}$	$\tau_{r_s^2,m}$	$\tau_{U,C}$	$\tau_{U,m}$	$\tau_{C,m}$
Gupta et al. (2013).	4	Sales at Month 1	1.00	1.00	1.00	1.00	1.00	1.00
Gupta et al. (2013).	4	Sales at Month 2	0.67	0.67	0.67	1.00	1.00	1.00
Gupta et al. (2013).	4	Sales at Month 3	0.33	-0.33	1.00	0.33	0.33	-0.33
Gupta et al. (2013).	4	Sales at Month 4	0.33	-0.33	1.00	-0.33	0.33	-0.33
Gupta et al. (2013).	4	Sales at Month 5	0.67	0.67	1.00	0.33	0.67	0.67
Gupta et al. (2013).	5	Sales at Month 1	0.20	0.20	0.20	1.00	1.00	1.00
Gupta et al. (2013).	5	Sales at Month 2	0.20	0.20	0.20	1.00	1.00	1.00

Article	Number of Predictors	Dependent Variable	$\tau_{r_s^2,U}$	$\tau_{r_s^2,C}$	$\tau_{r_s^2,m}$	$\tau_{U,C}$	$\tau_{U,m}$	$\tau_{C,m}$
Gupta et al. (2013).	5	Sales at Month 3	0.60	0.20	0.80	0.60	0.40	0.00
Gupta et al. (2013).	5	Sales at Month 4	0.20	0.00	0.60	0.40	0.60	0.40
Gupta et al. (2013).	5	Sales at Month 5	0.20	0.60	1.00	-0.20	0.20	0.60
Hannah et al. (2013).	4	Adaptive decision-making	0.00	1.00	0.33	0.00	0.67	0.33
Harris et al. (2008).	8	Pay level satisfaction	0.29	-0.43	0.21	0.29	0.64	0.07
Hay et al. (2011).	4	Parental reports of infance aggressiveness	0.67	1.00	1.00	0.67	0.67	1.00

Article	Number of Predictors	Dependent Variable	$\tau_{r_s^2,U}$	$\tau_{r_s^2,C}$	$\tau_{r_s^2,m}$	$\tau_{U,C}$	$\tau_{U,m}$	$\tau_{C,m}$
Hay et al. (2011).	4	Observed use of instrumental force	0.33	0.33	1.00	0.33	0.33	0.33
Hay et al. (2011).	4	Observed use of bodily force	0.67	0.67	0.67	1.00	1.00	1.00
Heimeriks et al. (2012).	11	Acquisition integration performance	0.53	0.78	0.85	0.31	0.67	0.64
Heimeriks et al. (2012).	11	Risk management practices	0.24	0.82	0.64	0.35	0.53	0.60
Hewlin (2009).	4	Nonparticipative environments	0.67	0.00	1.00	-0.33	0.67	0.00

Article	Number of Predictors	Dependent Variable	$\tau_{r_s^2,U}$	$\tau_{r_s^2,C}$	$\tau_{r_s^2,m}$	$\tau_{U,C}$	$\tau_{U,m}$	$\tau_{C,m}$
Hinkin & Schriesheim (2008).	4	Supervisor effectiveness	0.00	0.67	0.00	-0.33	1.00	-0.33
Hinkin & Schriesheim (2008).	4	Supervisor satisfaction	0.33	1.00	0.33	0.33	1.00	0.33
Hinkin & Schriesheim (2008).	3	Role clarity	1.00	0.33	1.00	0.33	1.00	0.33
Hirschfeld et al. (2013).	6	Within-team participation rate	0.20	0.47	0.60	-0.07	0.60	0.33
Hirschfeld et al. (2013).	10	Observed teamwork effectiveness	0.29	0.91	0.64	0.20	0.64	0.56

Article	Number of Predictors	Dependent Variable	$\tau_{r_s^2,U}$	$\tau_{r_s^2,C}$	$\tau_{r_s^2,m}$	$\tau_{U,C}$	$\tau_{U,m}$	$\tau_{C,m}$
Hirschfeld & Bernerth (2008).	4	Team mental efficacy	1.00	0.67	1.00	0.67	1.00	0.67
Hirschfeld & Bernerth (2008).	4	Team physical efficacy	1.00	0.00	1.00	0.00	1.00	0.00
Hirschfeld & Bernerth (2008).	8	Project X Phase 2 results	0.29	0.79	0.64	0.07	0.64	0.43
Hirschfeld & Bernerth (2008).	8	Problem solving results	0.21	0.21	0.50	0.57	0.71	0.43
Hirschfeld & Bernerth (2008).	8	Field operations results	0.50	0.21	0.57	0.14	0.93	0.21
Hirschfeld & Bernerth (2008).	9	Internal social cohesion	0.17	0.67	0.94	0.28	0.22	0.61
Hirschfeld & Bernerth (2008).	10	Observed teamwork effectiveness	0.47	0.69	0.73	0.16	0.64	0.42

Article	Number of Predictors	Dependent Variable	$\tau_{r_s^2,U}$	$\tau_{r_s^2,C}$	$\tau_{r_s^2,m}$	$\tau_{U,C}$	$\tau_{U,m}$	$\tau_{C,m}$
Hult et al. (2004).	3	Knowledge acquisition	1.00	1.00	1.00	1.00	1.00	1.00
Hult et al. (2004).	4	Information distribution	0.33	1.00	0.67	0.33	0.67	0.67
Hult et al. (2004).	5	Shared meaning	0.40	1.00	1.00	0.40	0.40	1.00
Hult et al. (2004).	6	Subjective cycle time	0.60	0.47	0.60	0.07	1.00	0.07
Ilies & Judge (2003).	5	Job satisfaction	0.40	0.80	0.80	0.20	0.60	0.60
Jackson et al. (2006).	6	Citizenship behavior	0.73	0.07	0.87	0.33	0.87	0.20
Jackson et al. (2006).	6	Counter-productive behavior	0.47	0.47	0.73	0.73	0.73	0.47

Article	Number of Predictors	Dependent Variable	$\tau_{r_s^2,U}$	$\tau_{r_s^2,C}$	$\tau_{r_s^2,m}$	$\tau_{U,C}$	$\tau_{U,m}$	$\tau_{C,m}$
Jackson et al. (2006).	6	Withdrawal behavior	0.60	-0.20	0.73	-0.07	0.87	-0.20
Jackson et al. (2006).	4	Task Performance	1.00	0.67	1.00	0.67	1.00	0.67
Janssen & Van Yperen (2004).	6	In-role job performance	0.47	0.33	0.47	-0.20	0.47	0.07
Janssen & Van Yperen (2004).	6	Innovative job performance	0.73	0.60	0.60	0.33	0.87	0.20
Janssen & Van Yperen (2004).	6	Job satisfaction	0.73	1.00	0.87	0.73	0.87	0.87
Janssen & Van Yperen (2004).	5	Leader-member exchange	0.80	0.40	1.00	0.60	0.80	0.40
Jehn et al. (2010).	4	Group performance score	1.00	0.67	0.67	0.67	0.67	0.33

Article	Number of Predictors	Dependent Variable	$\tau_{r_s^2,U}$	$\tau_{r_s^2,C}$	$\tau_{r_s^2,m}$	$\tau_{U,C}$	$\tau_{U,m}$	$\tau_{C,m}$
Jehn et al. (2010).	4	Creativity	0.67	-0.67	1.00	-1.00	0.67	-0.67
Jehn et al. (2010).	4	Group performance score	0.33	0.00	0.67	0.67	0.67	0.33
Jehn et al. (2010).	4	Creativity	0.33	0.33	0.67	0.33	0.67	0.67
Jiang et al. (2012).	3	Human Capital	1.00	1.00	1.00	1.00	1.00	1.00
Jiang et al. (2012).	3	Employee Motivation	1.00	1.00	1.00	1.00	1.00	1.00
Johnson, Morgeson, Ilgen, Meyer & Lloyd (2006).	6	Job satisfaction	0.87	0.87	1.00	0.73	0.87	0.87

Article	Number of Predictors	Dependent Variable	$\tau_{r_s^2,U}$	$\tau_{r_s^2,C}$	$\tau_{r_s^2,m}$	$\tau_{U,C}$	$\tau_{U,m}$	$\tau_{C,m}$
Judge et al. (2007).	8	Work-related performance	0.50	0.57	0.64	0.07	0.86	0.21
Judge et al. (2007).	7	Work-related performance	0.52	0.24	0.62	-0.05	0.90	0.05
Judge et al.(2006).	6	Leadership—self	0.33	0.33	0.47	-0.33	0.87	-0.20
Judge et al.(2006).	6	Leadership—other	0.20	0.33	0.33	-0.20	0.87	-0.07
Judge et al.(2006).	6	Leadership—self	-0.07	0.73	0.20	-0.33	0.73	-0.07
Judge et al.(2006).	6	Leadership—other	-0.07	0.20	0.47	0.20	0.47	0.20
Judge et al.(2006).	6	Workplace deviance—self	0.87	0.47	0.87	0.33	1.00	0.33

Article	Number of Predictors	Dependent Variable	$\tau_{r_s^2,U}$	$\tau_{r_s^2,C}$	$\tau_{r_s^2,m}$	$\tau_{U,C}$	$\tau_{U,m}$	$\tau_{C,m}$
Judge et al.(2006).	6	Workplace deviance—other	0.87	0.07	0.87	0.20	1.00	0.20
Judge et al.(2006).	6	Contextual performance—self	0.60	0.87	0.73	0.47	0.87	0.60
Judge et al.(2006).	6	Contextual performance—other	0.60	0.60	0.73	0.47	0.87	0.60
Judge et al.(2006).	6	Task performance—self	0.60	0.73	0.87	0.33	0.73	0.60
Judge et al.(2006).	6	Task performance—other	0.60	0.47	0.73	0.87	0.87	0.73
Kim & Jensen (2014).	25	foreign box office performance	0.45	0.89	0.71	0.38	0.67	0.63

Article	Number of Predictors	Dependent Variable	$\tau_{r_s^2,U}$	$\tau_{r_s^2,C}$	$\tau_{r_s^2,m}$	$\tau_{U,C}$	$\tau_{U,m}$	$\tau_{C,m}$
Kim & Jensen (2014).	21	foreign box office performance	0.44	0.77	0.74	0.25	0.68	0.57
Kirkman et al. (2004).	3	Process improvement	1.00	0.33	1.00	0.33	1.00	0.33
Kirkman et al. (2004).	3	Team customer satisfaction	1.00	0.33	1.00	0.33	1.00	0.33
Klehe & Anderson (2007).	7	Typical Performance 1	0.71	0.81	0.90	0.52	0.81	0.71
Klehe & Anderson (2007).	9	Typical Performance 2	0.39	0.94	0.61	0.33	0.78	0.56

Article	Number of Predictors	Dependent Variable	$\tau_{r_s^2,U}$	$\tau_{r_s^2,C}$	$\tau_{r_s^2,m}$	$\tau_{U,C}$	$\tau_{U,m}$	$\tau_{C,m}$
Klehe & Anderson (2007).	5	Typical Performance 1	0.80	1.00	0.80	0.80	1.00	0.80
Klehe & Anderson (2007).	5	Typical Performance 2	0.60	0.60	0.80	0.20	0.80	0.40
Klehe & Anderson (2007).	3	Maximum Perforance	1.00	1.00	1.00	1.00	1.00	1.00
Kraimer et al. (2012).	9	International Employee Identity	0.56	0.44	0.83	0.11	0.72	0.39
Kwong & Wong (2014).	5	escalation allocation	0.60	1.00	1.00	0.60	0.60	1.00

Article	Number of Predictors	Dependent Variable	$\tau_{r_s^2,U}$	$\tau_{r_s^2,C}$	$\tau_{r_s^2,m}$	$\tau_{U,C}$	$\tau_{U,m}$	$\tau_{C,m}$
Kwong & Wong (2014).	4	escalation allocation	0.67	1.00	0.67	0.67	1.00	0.67
Lai et al. (2009).	3	Acceptance	1.00	-0.33	1.00	-0.33	1.00	-0.33
Leavitt et al. (2012).	3	Sphere of concern	1.00	1.00	1.00	1.00	1.00	1.00
Lee et al.(2014).	8	speed	0.79	0.36	0.79	0.29	1.00	0.29
Lee et al.(2014).	8	accuracy	0.57	0.50	0.79	0.36	0.79	0.57
Lee et al. (2004).	4	Performance (in-role)	0.33	0.00	0.67	0.67	0.67	0.33
Lee et al. (2004).	4	OCB (extra-role)	0.00	0.33	0.00	0.00	1.00	0.00
Lee et al. (2004).	4	Volitional absences	1.00	1.00	1.00	1.00	1.00	1.00

Article	Number of Predictors	Dependent Variable	$\tau_{r_s^2,U}$	$\tau_{r_s^2,C}$	$\tau_{r_s^2,m}$	$\tau_{U,C}$	$\tau_{U,m}$	$\tau_{C,m}$
Lian et al. (2012).	8	interpersonal deviance at work	0.36	0.93	0.79	0.43	0.57	0.86
Lian et al. (2012).	8	interpersonal deviance at home	0.57	0.93	0.79	0.50	0.79	0.71
Lievens & Sackett (2012).	3	Internship performance	1.00	0.33	1.00	0.33	1.00	0.33
Lievens & Sackett (2012).	3	Job performance	1.00	0.33	1.00	0.33	1.00	0.33
Lim & Ployhart (2004).	5	Transformational leadership	0.40	1.00	0.60	0.40	0.80	0.60
Madjar et al.(2011).	21	Radical Creativity	0.48	0.68	0.71	0.40	0.74	0.50

Article	Number of Predictors	Dependent Variable	$\tau_{r_s^2,U}$	$\tau_{r_s^2,C}$	$\tau_{r_s^2,m}$	$\tau_{U,C}$	$\tau_{U,m}$	$\tau_{C,m}$
Madjar et al.(2011).	21	Incremental Creativity	0.42	0.59	0.73	0.58	0.69	0.63
Madjar et al.(2011).	21	Routine performance	0.27	0.59	0.59	0.24	0.66	0.35
McDonald & Westphal (2010).	11	identification with corporate elite	0.35	0.42	0.56	0.27	0.78	0.49
Moon et al. (2008).	6	Taking charge	0.33	0.07	0.73	0.20	0.60	0.33
Moon et al. (2008).	6	Taking charge (cow)	0.73	0.60	0.87	0.60	0.87	0.47
Moon et al. (2008).	6	Taking charge (sup)	0.47	0.87	0.73	0.60	0.73	0.60
Mumford et al. (2008).	7	task role performance	0.52	0.05	0.62	0.33	0.90	0.24

Article	Number of Predictors	Dependent Variable	$\tau_{r_s^2,U}$	$\tau_{r_s^2,C}$	$\tau_{r_s^2,m}$	$\tau_{U,C}$	$\tau_{U,m}$	$\tau_{C,m}$
Mumford et al. (2008).	7	social role performance	0.71	0.71	1.00	0.81	0.71	0.71
Mumford et al. (2008).	7	overall team performance	0.71	0.14	0.71	0.43	1.00	0.43
Mumford et al. (2008).	9	task role performance	0.39	0.50	0.61	0.22	0.78	0.44
Mumford et al. (2008).	9	social role performance	0.44	0.72	1.00	0.39	0.44	0.72
Mumford et al. (2008).	9	overall team performance	0.22	0.50	0.56	0.17	0.67	0.50
Nifadkar et al. (2012).	11	Feedback Seeking	0.09	0.82	0.60	-0.02	0.42	0.49
Nifadkar et al. (2012).	11	Interaction Avoidance	0.45	0.45	0.75	0.05	0.71	0.27

Article	Number of Predictors	Dependent Variable	$\tau_{r_s^2,U}$	$\tau_{r_s^2,C}$	$\tau_{r_s^2,m}$	$\tau_{U,C}$	$\tau_{U,m}$	$\tau_{C,m}$
Oh & Kilduff (2008).	6	Direct brokerage	0.87	0.60	1.00	0.73	0.87	0.60
Oh & Kilduff (2008).	7	Indirect brokerage	0.71	0.81	0.62	0.52	0.90	0.43
Porath & Bateman (2006).	4	Learning goal orientation	0.67	0.33	0.67	0.00	1.00	0.00
Porath & Bateman (2006).	4	Performance-prove goal orientation	1.00	0.33	1.00	0.33	1.00	0.33
Porath & Bateman (2006).	4	Performance-avoid goal orientation	1.00	0.67	1.00	0.67	1.00	0.67

Article	Number of Predictors	Dependent Variable	$\tau_{r_s^2,U}$	$\tau_{r_s^2,C}$	$\tau_{r_s^2,m}$	$\tau_{U,C}$	$\tau_{U,m}$	$\tau_{C,m}$
Porath & Bateman (2006).	4	Performance	0.33	-0.33	0.67	0.33	0.67	0.00
Porath & Bateman (2006).	5	Performance	-0.20	0.20	0.60	0.20	0.20	-0.20
Ragins et al. (2007).	8	degree of disclosure	0.50	0.79	0.71	0.57	0.79	0.79
Ragins et al. (2007).	8	Fear of disclosure	0.86	0.93	1.00	0.79	0.86	0.93
Raja et al. (2004).	6	Intentions to quit	0.33	0.87	0.60	0.20	0.73	0.47
Raja et al. (2004).	6	Affective commitment	0.33	0.87	0.47	0.20	0.87	0.33

Article	Number of Predictors	Dependent Variable	$\tau_{r_s^2,U}$	$\tau_{r_s^2,C}$	$\tau_{r_s^2,m}$	$\tau_{U,C}$	$\tau_{U,m}$	$\tau_{C,m}$
Raja et al. (2004).	6	Job satisfaction	0.20	0.87	0.60	0.07	0.60	0.47
Raja et al. (2004).	5	Intentions to quit	1.00	0.60	1.00	0.60	1.00	0.60
Raja et al. (2004).	5	Affective commitment	0.40	0.40	0.40	-0.20	1.00	-0.20
Raja et al. (2004).	5	Job satisfaction	0.00	1.00	0.40	0.00	0.60	0.40
Raja et al. (2004).	6	Intentions to quit	0.20	0.87	0.60	0.07	0.60	0.47
Raja et al. (2004).	6	Affective commitment	0.47	1.00	0.73	0.47	0.73	0.73
Raja et al. (2004).	6	Job satisfaction	0.20	0.73	0.47	-0.07	0.47	0.20

Article	Number of Predictors	Dependent Variable	$\tau_{r_s^2,U}$	$\tau_{r_s^2,C}$	$\tau_{r_s^2,m}$	$\tau_{U,C}$	$\tau_{U,m}$	$\tau_{C,m}$
Raja et al. (2004).	12	Intentions to quit	0.15	0.85	0.58	0.00	0.52	0.42
Raja et al. (2004).	12	Affective commitment	0.52	0.91	0.61	0.42	0.85	0.52
Raja et al. (2004).	12	Job satisfaction	0.27	0.91	0.79	0.18	0.48	0.70
Raja et al. (2004).	10	Intentions to quit	0.16	0.87	0.56	0.02	0.60	0.42
Raja et al. (2004).	10	Affective commitment	0.69	0.91	0.69	0.60	0.73	0.60
Raja et al. (2004).	10	Job satisfaction	0.20	0.91	0.42	0.11	0.69	0.33
Raub & Liao (2012).	8	Aggregated PCSP	0.50	0.36	0.86	0.57	0.64	0.36

Article	Number of Predictors	Dependent Variable	$\tau_{r_s^2,U}$	$\tau_{r_s^2,C}$	$\tau_{r_s^2,m}$	$\tau_{U,C}$	$\tau_{U,m}$	$\tau_{C,m}$
Raub & Liao (2012).	10	Customer service satisfaction	0.29	0.33	0.56	-0.02	0.73	0.16
Raver et al. (2010).	3	Organizational commitment	1.00	0.33	1.00	0.33	1.00	0.33
Raver et al. (2010).	3	Job satisfaction	1.00	1.00	1.00	1.00	1.00	1.00
Raver et al. (2010).	3	Turnover intentions	0.33	-0.33	1.00	-1.00	0.33	-0.33
Raver et al. (2010).	3	Organizational commitment	1.00	0.33	1.00	0.33	1.00	0.33
Raver et al. (2010).	3	Job satisfaction	1.00	1.00	1.00	1.00	1.00	1.00
Raver et al. (2010).	3	Turnover intentions	1.00	0.33	1.00	0.33	1.00	0.33

Article	Number of Predictors	Dependent Variable	$\tau_{r_s^2,U}$	$\tau_{r_s^2,C}$	$\tau_{r_s^2,m}$	$\tau_{U,C}$	$\tau_{U,m}$	$\tau_{C,m}$
Reynolds (2008).	7	Charitable giving	0.52	0.62	0.90	0.52	0.62	0.71
Reynolds (2008).	7	Self-reported moral behavior	0.81	0.90	1.00	0.71	0.81	0.90
Reynolds (2008).	7	Others' moral behavior	0.81	0.81	0.90	0.81	0.90	0.90
Reynolds (2008).	4	Moral awareness ("present" scenario)	0.67	0.33	1.00	0.00	0.67	0.33
Reynolds (2008).	4	Moral awareness ("absent" scenario)	0.67	0.67	0.67	0.33	1.00	0.33
Reynolds et al. (2010).	5	Considerations for shareholders	1.00	0.00	1.00	0.00	1.00	0.00

Article	Number of Predictors	Dependent Variable	$\tau_{r_s^2,U}$	$\tau_{r_s^2,C}$	$\tau_{r_s^2,m}$	$\tau_{U,C}$	$\tau_{U,m}$	$\tau_{C,m}$
Reynolds et al. (2010).	5	Libertarianism	1.00	1.00	1.00	1.00	1.00	1.00
Rhee & Fiss (2014).	16	stock market reaction	0.73	0.55	0.75	0.82	0.98	0.80
Rhee & Fiss (2014).	15	stock market reaction	0.77	0.64	0.85	0.79	0.92	0.79
Rhee & Fiss (2014).	14	stock market reaction	0.87	0.71	0.96	0.76	0.91	0.76
Rhee & Fiss (2014).	14	stock market reaction	0.65	0.45	0.69	0.80	0.96	0.76
Rhee & Fiss (2014).	13	stock market reaction	0.74	0.51	0.79	0.77	0.95	0.72
Richards et al. (2011).	12	Surface acting	0.52	0.52	0.70	0.58	0.82	0.58

Article	Number of Predictors	Dependent Variable	$\tau_{r_s^2,U}$	$\tau_{r_s^2,C}$	$\tau_{r_s^2,m}$	$\tau_{U,C}$	$\tau_{U,m}$	$\tau_{C,m}$
Richards et al. (2011).	12	Instrumental support seeking	0.58	0.85	0.76	0.42	0.82	0.61
Richards et al. (2011).	12	Emotional support seeking	0.67	0.79	0.79	0.45	0.82	0.58
Richards et al. (2011).	12	Turnover intention	0.21	0.94	0.48	0.15	0.73	0.42
Richards et al. (2011).	12	organizational citizenship behaviors directed at the organization	0.52	0.97	0.64	0.48	0.82	0.61
Salamon & Robinson (2008).	6	Responsibility norms	0.73	1.00	0.87	0.73	0.87	0.87

Article	Number of Predictors	Dependent Variable	$\tau_{r_s^2,U}$	$\tau_{r_s^2,C}$	$\tau_{r_s^2,m}$	$\tau_{U,C}$	$\tau_{U,m}$	$\tau_{C,m}$
Salamon & Robinson (2008).	7	Sales	0.33	0.24	0.62	0.14	0.71	0.24
Salamon & Robinson (2008).	7	Customer service	0.05	0.81	0.52	0.24	0.52	0.52
Saparito et al. (2004).	14	Likelihood of switching	0.27	0.45	0.47	0.65	0.80	0.80
Schuelke et al. (2009).	3	Links	1.00	1.00	1.00	1.00	1.00	1.00
Schuelke et al. (2009).	3	Coherence	1.00	1.00	1.00	1.00	1.00	1.00
Schuelke et al. (2009).	3	Closeness	0.33	0.33	1.00	-0.33	0.33	0.33

Article	Number of Predictors	Dependent Variable	$\tau_{r_s^2,U}$	$\tau_{r_s^2,C}$	$\tau_{r_s^2,m}$	$\tau_{U,C}$	$\tau_{U,m}$	$\tau_{C,m}$
Schuelke et al. (2009).	3	Correlation	1.00	0.33	1.00	0.33	1.00	0.33
Schuelke et al. (2009).	5	Skill acquisition	0.80	1.00	0.80	0.80	1.00	0.80
Schuelke et al. (2009).	5	Skill transfer	1.00	1.00	1.00	1.00	1.00	1.00
Schuelke et al. (2009).	5	Skill acquisition	1.00	1.00	0.80	1.00	0.80	0.80
Schuelke et al. (2009).	5	Skill transfer	0.80	1.00	0.80	0.80	1.00	0.80
Schuelke et al. (2009).	5	Skill acquisition	1.00	1.00	1.00	1.00	1.00	1.00
Schuelke et al. (2009).	5	Skill transfer	0.80	1.00	1.00	0.80	0.80	1.00

Article	Number of Predictors	Dependent Variable	$\tau_{r_s^2,U}$	$\tau_{r_s^2,C}$	$\tau_{r_s^2,m}$	$\tau_{U,C}$	$\tau_{U,m}$	$\tau_{C,m}$
Scott & Judge (2009).	5	Organizational citizenship behavior received by employee	0.80	0.80	1.00	0.60	0.80	0.80
Scott & Judge (2009).	5	Counterproductive work behavior received by employee	0.20	1.00	0.80	0.20	0.40	0.80
Shaffer et al. (2006).	5	Cultural adjustment	0.20	0.60	0.00	-0.20	0.80	-0.40
Shaffer et al. (2006).	5	Interaction adjustment	0.60	1.00	0.80	0.60	0.80	0.80
Shaffer et al. (2006).	5	Work adjustment	0.80	0.60	0.80	0.40	1.00	0.40

Article	Number of Predictors	Dependent Variable	$\tau_{r_s^2,U}$	$\tau_{r_s^2,C}$	$\tau_{r_s^2,m}$	$\tau_{U,C}$	$\tau_{U,m}$	$\tau_{C,m}$
Shaffer et al. (2006).	5	Withdrawal cognitions	0.60	0.60	0.80	0.60	0.80	0.80
Shaffer et al. (2006).	5	Contextual performance	0.00	0.80	0.80	-0.20	0.20	0.60
Shaffer et al. (2006).	5	Task performance	0.80	0.80	0.80	0.60	1.00	0.60
Shaffer et al. (2006).	4	Cultural adjustment	1.00	1.00	1.00	1.00	1.00	1.00
Shaffer et al. (2006).	4	Interaction adjustment	0.67	1.00	0.67	0.67	1.00	0.67
Shaffer et al. (2006).	4	Work adjustment	0.00	0.67	0.33	-0.33	0.67	0.00
Shaffer et al. (2006).	4	Withdrawal cognitions	0.33	0.67	0.33	0.00	1.00	0.00

Article	Number of Predictors	Dependent Variable	$\tau_{r_s^2,U}$	$\tau_{r_s^2,C}$	$\tau_{r_s^2,m}$	$\tau_{U,C}$	$\tau_{U,m}$	$\tau_{C,m}$
Shaffer et al. (2006).	4	Contextual performance	0.67	0.67	1.00	0.33	0.67	0.67
Shaffer et al. (2006).	4	Task performance	0.67	1.00	1.00	0.67	0.67	1.00
Shaffer et al. (2006).	4	Cultural adjustment	0.67	1.00	1.00	0.67	0.67	1.00
Shaffer et al. (2006).	4	Interaction adjustment	1.00	1.00	1.00	1.00	1.00	1.00
Shaffer et al. (2006).	4	Work adjustment	1.00	0.67	1.00	0.67	1.00	0.67
Shaffer et al. (2006).	4	Withdrawal cognitions	1.00	0.67	1.00	0.67	1.00	0.67
Shaffer et al. (2006).	4	Contextual performance	1.00	0.33	1.00	0.33	1.00	0.33

Article	Number of Predictors	Dependent Variable	$\tau_{r_s^2,U}$	$\tau_{r_s^2,C}$	$\tau_{r_s^2,m}$	$\tau_{U,C}$	$\tau_{U,m}$	$\tau_{C,m}$
Shaffer et al. (2006).	4	Task performance	1.00	1.00	1.00	1.00	1.00	1.00
Shapiro et al. (2011).	19	Employee's turnover intentions	0.32	0.29	0.64	0.43	0.68	0.32
Shapiro et al. (2011).	19	Employee's psychological withdrawal	0.49	0.75	0.68	0.43	0.80	0.56
Shapiro et al. (2011).	16	Leader–member exchange	0.47	0.60	0.72	0.43	0.75	0.58
Simons et al. (2007).	7	Trust in manager	0.24	1.00	0.62	0.24	0.62	0.62
Simons et al. (2007).	7	Interpersonal justice	0.62	0.81	0.71	0.81	0.90	0.90

Article	Number of Predictors	Dependent Variable	$\tau_{r_s^2,U}$	$\tau_{r_s^2,C}$	$\tau_{r_s^2,m}$	$\tau_{U,C}$	$\tau_{U,m}$	$\tau_{C,m}$
Simons et al. (2007).	7	Satisfaction	0.52	0.90	0.81	0.62	0.71	0.71
Simons et al. (2007).	7	Commitment	0.81	0.71	1.00	0.52	0.81	0.71
Simons et al. (2007).	7	Intent to stay	0.81	0.52	1.00	0.71	0.81	0.52
Slaughter et al. (2014).	14	initial belief confidence	0.43	0.91	0.67	0.38	0.67	0.58
Strauss et al. (2012).	8	Proactive career behavior	0.93	0.86	0.93	0.79	1.00	0.79
Strauss et al. (2012).	5	Proactive career behavior	0.60	1.00	1.00	0.60	0.60	1.00
Strauss et al. (2012).	6	Proactive career behavior Time 2	0.60	0.87	1.00	0.73	0.60	0.87

Article	Number of Predictors	Dependent Variable	$\tau_{r_s^2,U}$	$\tau_{r_s^2,C}$	$\tau_{r_s^2,m}$	$\tau_{U,C}$	$\tau_{U,m}$	$\tau_{C,m}$
Summers et al. (2012).	5	Task performance, time 3	1.00	0.80	1.00	0.80	1.00	0.80
Takeuchi et al. (2007).	13	Collective human capital	0.36	0.33	0.62	0.62	0.74	0.46
Takeuchi et al. (2007).	13	Degree of establishment social exchange	0.41	0.87	0.72	0.38	0.64	0.69
Takeuchi et al. (2007).	13	Collective human capital	0.38	0.26	0.72	0.51	0.67	0.28
Takeuchi et al. (2007).	13	Degree of establishment social exchange	0.67	0.28	0.79	0.26	0.82	0.28

Article	Number of Predictors	Dependent Variable	$\tau_{r_s^2,U}$	$\tau_{r_s^2,C}$	$\tau_{r_s^2,m}$	$\tau_{U,C}$	$\tau_{U,m}$	$\tau_{C,m}$
Takeuchi et al. (2007).	15	Relative establishment performance	0.24	0.39	0.77	0.47	0.47	0.43
Takeuchi et al. (2007).	15	Relative establishment performance	0.09	0.16	0.52	0.05	0.52	-0.01
Tay et al. (2006).	11	Interview success	0.13	0.20	0.35	0.42	0.78	0.42
Tay et al. (2006).	10	Initial Interview Self Elficacy	-0.02	0.11	0.47	0.16	0.51	-0.07
Trevor & Nyberg (2008).	17	turnover	0.29	0.75	0.63	0.51	0.60	0.65
Trevor & Nyberg (2008).	16	turnover	0.32	0.80	0.65	0.45	0.60	0.68

Article	Number of Predictors	Dependent Variable	$\tau_{r_s^2,U}$	$\tau_{r_s^2,C}$	$\tau_{r_s^2,m}$	$\tau_{U,C}$	$\tau_{U,m}$	$\tau_{C,m}$
Trevor & Nyberg (2008).	16	commitment	0.42	0.58	0.73	0.43	0.65	0.45
van Hooft & Noordzij (2009).	8	Job search behavior	0.14	0.71	0.79	0.14	0.36	0.64
van Hooft & Noordzij (2009).	7	Job search intention	0.81	0.90	0.90	0.71	0.90	0.81
Van Hoye & Lievens (2009).	4	Positive word-of-mouth	1.00	1.00	1.00	1.00	1.00	1.00
Van Hoye & Lievens (2009).	4	Negative word-of-mouth	1.00	1.00	1.00	1.00	1.00	1.00
Van Hoye & Lievens (2009).	7	Organizational attractiveness	0.43	0.90	0.52	0.33	0.71	0.43
Van Iddekinge et al. (2011).	6	Technical knowledge	0.20	0.07	0.60	0.60	0.33	0.47

Article	Number of Predictors	Dependent Variable	$\tau_{r_s^2,U}$	$\tau_{r_s^2,C}$	$\tau_{r_s^2,m}$	$\tau_{U,C}$	$\tau_{U,m}$	$\tau_{C,m}$
Van Iddekinge et al. (2011).	6	Interpersonal knowledge	0.20	0.60	0.60	0.60	0.60	0.73
Van Iddekinge et al. (2011).	6	Task proficiency	0.47	0.20	0.87	0.73	0.60	0.33
Van Iddekinge et al. (2011).	6	Effort	0.47	0.47	0.47	0.73	1.00	0.73
Van Iddekinge et al. (2011).	6	Continuance intentions	0.60	0.33	0.87	-0.07	0.73	0.20
Wallace et al. (2006).	4	Safety climate	1.00	0.67	1.00	0.67	1.00	0.67
Wallace et al. (2006).	5	Accidents	0.40	1.00	0.80	0.40	0.60	0.80
Wallace et al. (2006).	4	Safety climate	1.00	0.67	1.00	0.67	1.00	0.67

Article	Number of Predictors	Dependent Variable	$\tau_{r_s^2,U}$	$\tau_{r_s^2,C}$	$\tau_{r_s^2,m}$	$\tau_{U,C}$	$\tau_{U,m}$	$\tau_{C,m}$
Wallace et al. (2006).	5	Accidents	0.40	0.80	0.80	0.60	0.60	1.00
Walters et al. (2010).	16	holding period returns	0.57	0.63	0.73	0.53	0.73	0.47
Walters et al. (2010).	17	holding period returns	0.56	0.76	0.74	0.56	0.71	0.59
Zhang & Peterson (2011).	7	Team performance	0.62	0.81	0.81	0.43	0.81	0.62
Zhang & Peterson (2011).	6	Advice network density	0.87	0.60	0.87	0.47	1.00	0.47