

ON THE USE OF POLYNOMIAL REGRESSION EQUATIONS AS AN ALTERNATIVE TO DIFFERENCE SCORES IN ORGANIZATIONAL RESEARCH

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For decades, difference scores have been widely used in studies of congruence in organizational research. Although methodological problems with difference scores are well known, few viable alternatives have been proposed. One alternative involves the use of polynomial regression equations, which permit direct tests of the relationships difference scores are intended to represent. Unfortunately, coefficients from polynomial regression equations are often difficult to interpret. We used response surface methodology to develop an interpretive framework and illustrate it using data from a well-known person-environment study. Several important findings not reported in the original study emerged.

For decades, difference scores have been widely used in both micro and macro organizational research. Typically, these scores have consisted of the algebraic, absolute, or squared difference between two component measures (e.g., Alexander & Randolph, 1985; Dougherty & Pritchard, 1985; French, Caplan, & Harrison, 1982; Rice, McFarlin, & Bennett, 1989; Tubbs & Dahl, 1991; Turban & Jones, 1988) or the sum of absolute or squared differences between profiles of component measures (e.g., Drazin & Van de Ven, 1985; Gresov, 1989; Rounds, Dawis, & Lofquist, 1987; Sparrow, 1989; Turban & Jones, 1988; Vancouver & Schmitt, 1991; Venkatraman, 1990; Venkatraman & Prescott, 1990; Zalesny & Kirsch, 1989). In most cases, difference scores are used to represent congruence (i.e., fit, match, similarity, or agreement) between two constructs, which is then viewed as a predictor of some outcome (Edwards, 1991; Mowday, 1987; Wanous, Poland, Premack, & Davis, 1992; Van de Ven & Drazin, 1985).

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As is widely known, difference scores suffer from numerous substantive and methodological problems (Cronbach & Furby, 1970; Edwards, *in press*; Johns, 1981). An alternative procedure involves the use of polynomial regression equations containing the component measures composing the difference and certain higher-order terms, such as the squares of both component measures and their product (Edwards, *in press*). These equations permit a researcher to avoid many problems associated with difference scores but nonetheless obtain direct tests of conceptual models relevant to the study of congruence. Despite their advantages, polynomial equations often yield results that are difficult to interpret, particularly when their coefficients deviate from patterns corresponding to difference scores, as is usually the case (Edwards, 1992, *in press*; Edwards & Harrison, 1993). These interpretive difficulties are likely to prevent the widespread use of polynomial regression equations in the study of congruence, even though their use overcomes longstanding problems with difference scores.

This article provides a systematic framework for testing and interpreting polynomial regression equations within the study of congruence in organizational research. This framework draws from response surface methodology (Box & Draper, 1987; Khuri & Cornell, 1987), which permits precise description and evaluation of three-dimensional surfaces corresponding to polynomial regression equations. We illustrate the application of the framework using data from the classic study of person-environment (P-E) fit by French, Caplan, and Harrison (1982).

POLYNOMIAL REGRESSION AS AN ALTERNATIVE TO DIFFERENCE SCORES

Edwards (1991, *in press*; Edwards & Cooper, 1990) has described the polynomial regression procedure, showing how polynomial regression equations avoid problems with difference scores but permit direct tests of the relationships difference scores are intended to represent. This is illustrated by the following regression equation, which uses an algebraic difference as a single predictor (e.g., French et al., 1982; Kernan & Lord, 1990; Vance & Colella, 1990; Wanous & Lawler, 1972):

$$Z = b_0 + b_1(X - Y) + e. \quad (1)$$

In this equation, X and Y represent the two component measures comprising the difference, Z represents an outcome measure, and e represents a random disturbance term. The positive sign on b_1 indicates that the difference between X and Y is positively related to Z (see Figure 1a). Expanding this equation yields:

$$Z = b_0 + b_1X - b_1Y + e. \quad (2)$$

This expansion shows that Equation 1 implies a positive relationship between X and Z and a negative relationship between Y and Z (Figure 1b), with the constraint that the coefficients on X and Y are equal in magnitude but

opposite in sign. The following equation relaxes this constraint, allowing the coefficients on X and Y to take on whatever values maximize the variance explained in Z :

$$Z = b_0 + b_1X + b_2Y + e. \quad (3)$$

A somewhat more complicated equation uses the squared difference between two component measures (e.g., Caplan, Cobb, French, Harrison, & Pinneau, 1980; Dougherty & Pritchard, 1985; Tsui & O'Reilly, 1989):

$$Z = b_0 + b_1(X - Y)^2 + e. \quad (4)$$

The positive sign on b_1 indicates that Z increases as the difference between X and Y increases in either direction (Figure 1c). Expanding this equation yields:

$$Z = b_0 + b_1X^2 - 2b_1XY + b_1Y^2 + e. \quad (5)$$

This equation shows that a squared difference implies positive coefficients of equal magnitude on X^2 and Y^2 along with a negative coefficient twice as large in absolute magnitude on XY (Figure 1d). This equation also shows that Equation 4 implicitly contains curvilinear and interactive terms without appropriate lower-order terms (Cohen, 1978). Relaxing the constraints in Equation 5 and adding lower-order terms yields:

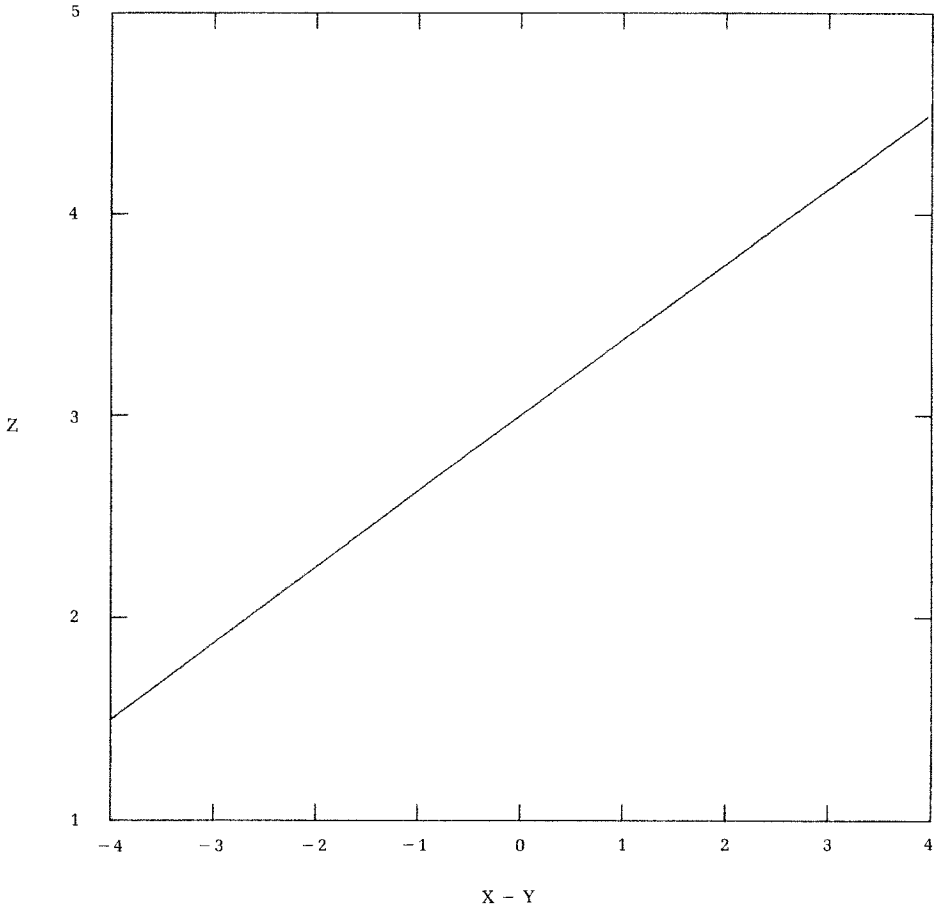
$$Z = b_0 + b_1X + b_2Y + b_3X^2 + b_4XY + b_5Y^2 + e. \quad (6)$$

This equation shows that a squared difference imposes four constraints: (1) The coefficient on X is 0, (2) the coefficient on Y is 0, (3) the coefficients on X^2 and Y^2 are equal, and (4) the coefficients on X^2 , XY , and Y^2 sum to 0; given the third constraint, this is equivalent to stating that the coefficient on XY is twice as large as the coefficient on either X^2 or Y^2 , but opposite in sign (cf. Edwards, in press). As will be shown later, Equation 6 can be used to test these constraints as well as to depict surfaces substantially more complex than that corresponding to the squared difference (Figure 1d).

Studies using the polynomial regression procedure (Edwards, 1992, in press; Edwards & Harrison, 1993) have yielded two general findings. First, most relationships of interest can be depicted using either a linear or a quadratic equation (Equations 3 and 6, respectively). Second, the constraints difference scores impose on these equations are usually rejected, making it necessary to interpret coefficients from the unconstrained linear and quadratic equations. Although interpreting coefficients from linear equations is relatively straightforward, coefficients from quadratic equations are often difficult to interpret, particularly when they deviate from the pattern implied by the squared difference (see Equation 5), as is usually the case. Unfortunately, studies using the polynomial regression procedure have offered little guidance for interpreting coefficients from quadratic equations when the constraints imposed by the squared difference are rejected.

To illustrate the difficulty of interpreting coefficients from quadratic regression equations, Table 1 reports six equations analyzed by Edwards and

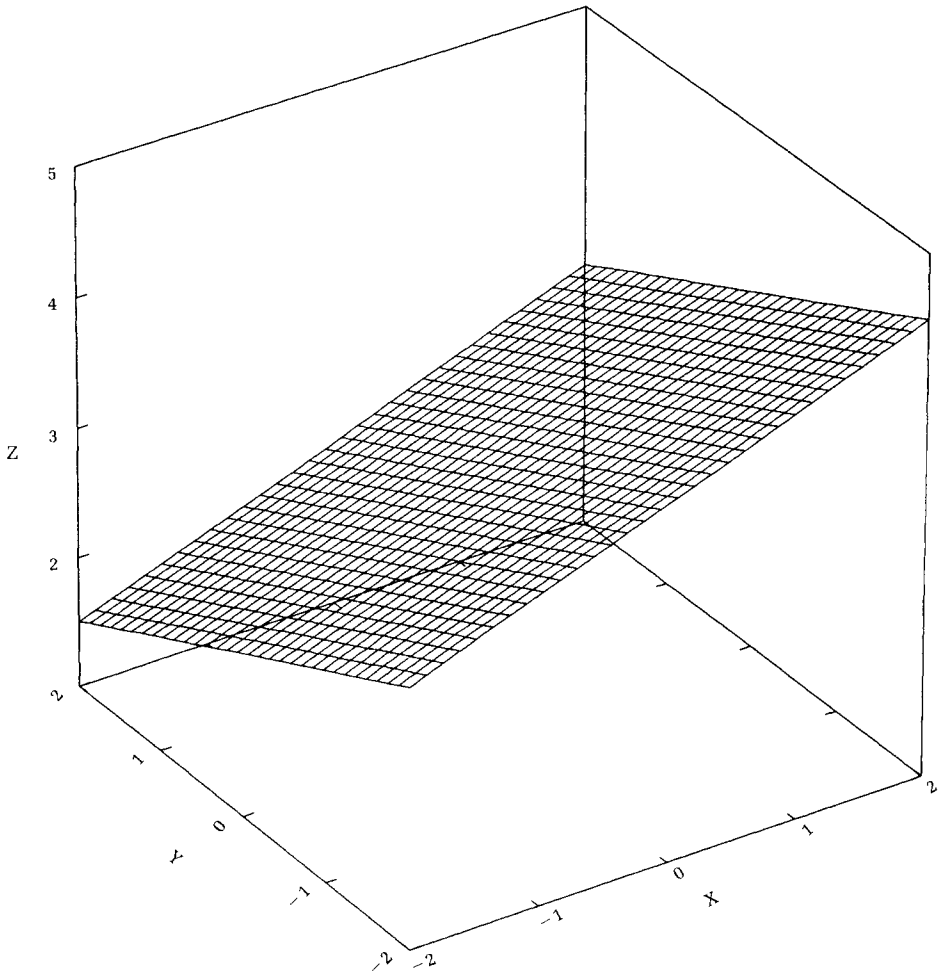
FIGURE 1a
Two-Dimensional Algebraic Difference Function



Harrison (1993). These equations used measures of the actual amount (X) and the desired amount (Y) of two job dimensions, job complexity and quantitative work load, to predict various measures of psychological strain. For comparison, we report results from the constrained equation for the squared difference (Equation 4) as well as from the unconstrained quadratic equation (Equation 6).

Results from all six constrained equations show that the coefficient from Equation 4 was positive and highly significant, suggesting that strain increased as the actual amounts of job complexity and quantitative work load deviated from desired amounts in either direction, as in Figure 1c. However, coefficients from the unconstrained equations did not correspond to the pattern predicted by the squared difference, which is as follows: (1) nonsignificant coefficients on X and Y ; (2) positive coefficients of equal magnitude on X^2 and Y^2 ; and (3) coefficients on X^2 , XY , and Y^2 that sum to 0. A formal

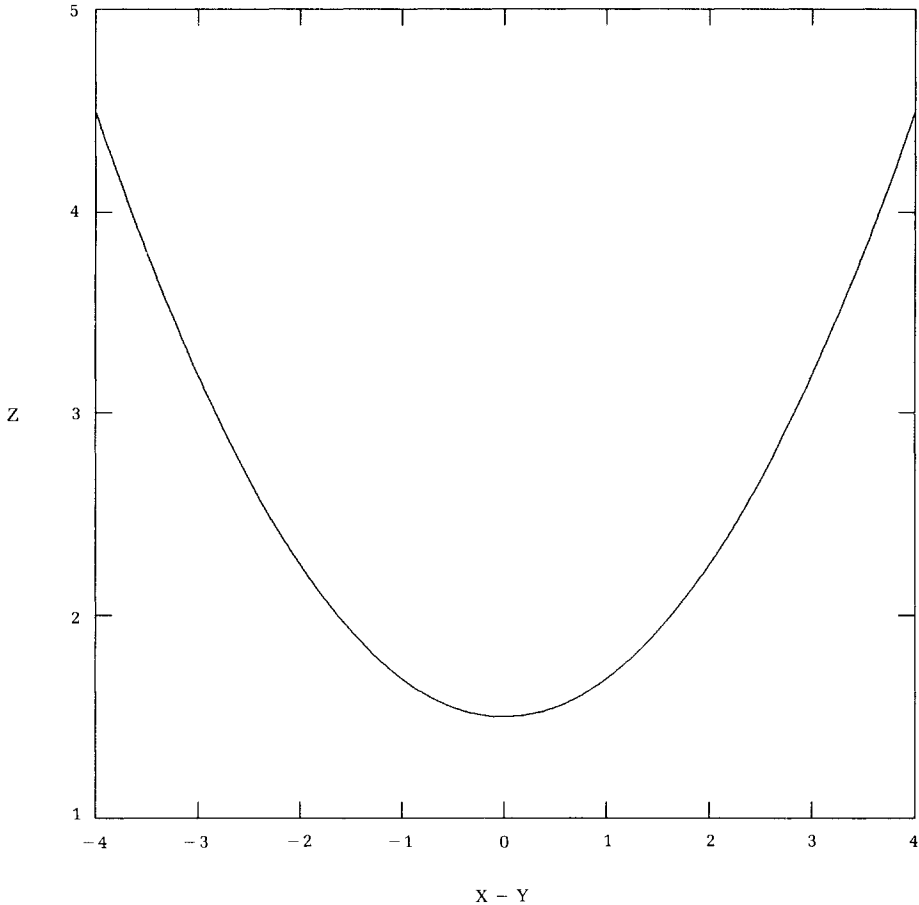
FIGURE 1b
Three-Dimensional Algebraic Difference Function



test of these constraints is presented in the last column of Table 1, which compares R^2 values from the constrained and unconstrained equations. In all six cases, the R^2 from the unconstrained equation was significantly higher than that from the constrained equation ($p < .05$), indicating that the constraints imposed by the squared difference were rejected.

The preceding results show that none of the unconstrained quadratic equations reported in Table 1 indicate a surface that corresponds to the squared difference (Figure 1d). Although the signs of the coefficients on X^2 , XY , and Y^2 were usually as predicted, the coefficient on Y^2 was significant in only one case, and coefficients on X and Y were often significantly different from 0. Because these coefficients did not follow the pattern corre-

FIGURE 1c
Two-Dimensional Squared Difference Function

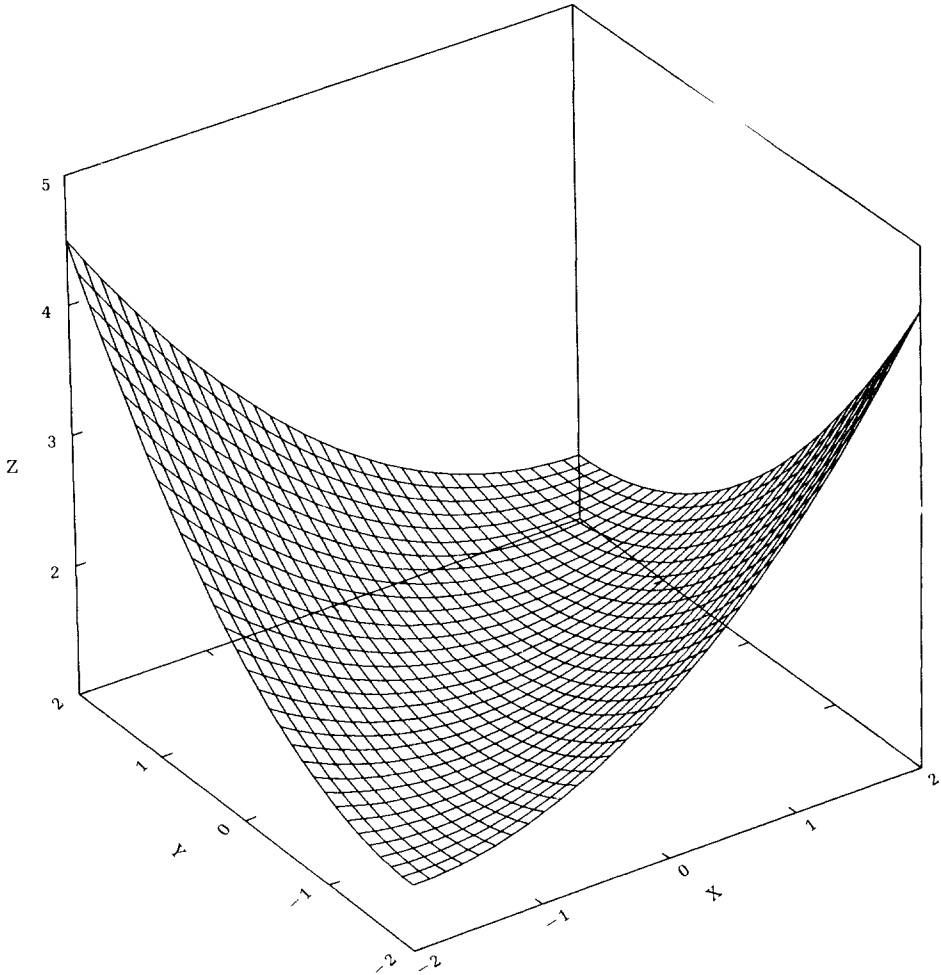


sponding to the squared difference, the joint relationship of X and Y with strain cannot be adequately depicted in two dimensions (i.e., Figure 1c), but instead must be viewed as a three-dimensional surface. Unfortunately, for most researchers, simply inspecting the signs and magnitudes of these coefficients reveals little as to the shape of the surface they represent. Of course, the coefficients can be used to plot the surface, but doing so would provide little basis for formally describing and testing the properties of the surfaces. This requires a more detailed and rigorous approach.

A FRAMEWORK FOR INTERPRETING QUADRATIC REGRESSION EQUATIONS IN THE STUDY OF CONGRUENCE

Response surface methodology (Box & Draper, 1987; Khuri & Cornell, 1987) provides the basis necessary for describing and testing the essential

FIGURE 1d
Three-Dimensional Squared Difference Function



features of surfaces corresponding to quadratic regression equations. We focused on three key features of these surfaces. The first is the stationary point (i.e., the point at which the slope of the surface is 0 in all directions), which corresponds to the overall minimum, maximum, or saddle point of the surface. The second feature is the principal axes of the surface, which run perpendicular to one another and intersect at the stationary point. For convex surfaces,¹ the upward curvature is greatest along the first principal

¹ A quadratic surface is convex if a line connecting any two points on the surface lies on or above that surface, whereas a quadratic surface is concave if a line connecting any two points on the surface lies on or below that surface (Chiang, 1974: 255).

TABLE 1
Results for Constrained and Unconstrained Equations^a

Job Dimension	Outcome	Constrained Equation			Unconstrained Equation			Difference in R ² s Between Constrained and Unconstrained Equations		
		(X - Y) ²	R ²	X	Y	XY	Y ²	R ²		
Job complexity	Job dissatisfaction	0.131**	.073**	-0.082	-0.117*	0.131**	-0.216**	0.068	.140**	11.89**
Job complexity	Work load dissatisfaction	0.108**	.037**	0.103	-0.226**	0.212**	-0.207**	0.023	.100**	10.68**
Job complexity	Boredom	0.193**	.116**	-0.467**	-0.023	0.154**	-0.206**	0.124**	.301**	40.51**
Job complexity	Depression	0.048**	.027**	0.023	-0.029	0.060**	-0.099**	0.014	.044**	2.83*
Job complexity	Anxiety	0.056**	.032**	0.096**	-0.009	0.047**	-0.153**	0.044	.058**	4.19**
Quantitative work load	Work load dissatisfaction	0.402**	.171**	0.377**	-0.455**	0.402**	-0.401*	-0.110	.322**	34.35**

^a Equations are from Edwards and Harrison (1993). N ranged from 617 to 625. For columns labeled X, Y, X², XY, and Y², table entries are unstandardized regression coefficients for equations with all predictors entered simultaneously. For the remaining two columns, R² is the squared multiple correlation coefficient, and the difference in R²s between the constrained and unconstrained equations is an F-test with four numerator degrees of freedom.

* p < .05
** p < .01

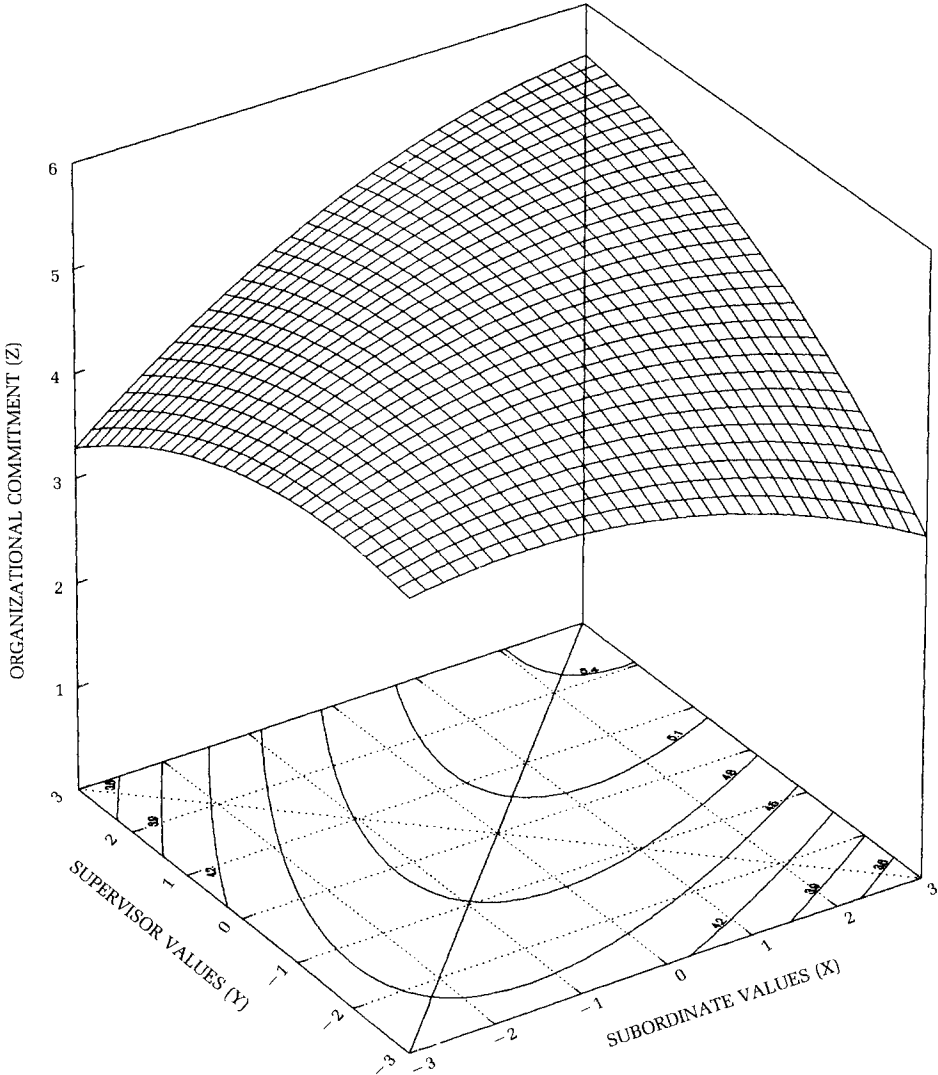
axis and least along the second principal axis. For concave surfaces, the downward curvature is least along the first principal axis and greatest along the second principal axis. For saddle-shaped surfaces, the upward curvature is greatest along the first principal axis, and the downward curvature is greatest along the second principal axis. Finally, the third feature is the slope of the surface along various lines of interest, such as the principal axes and the line along which the component variables are equal (the $Y = X$ line).

To illustrate these three features, Figures 2a–2d present four hypothetical surfaces, along with their corresponding quadratic equations. For each surface, contour lines are drawn on the X, Y plane to help clarify the shape of the surface. The stationary point and principal axes are also projected onto the X, Y plane, provided they lie within the range of the component measures. For these examples and the equations that follow, component measures are depicted in scale-centered form, that is, centered at their scale midpoints. Doing so simplifies certain calculations and facilitates the interpretation of the coefficients on X and Y , which then represent the slope of the surface at the center of the X, Y plane, where the origin of the x - and y -axes is located (Aiken & West, 1991; Edwards, in press; Jaccard, Turrisi, & Wan, 1990). It should be noted that these surfaces are not intended to represent the findings of a particular study or body of literature, but rather to illustrate how hypotheses from various areas of organizational research can be portrayed in terms of quadratic regression equations and their corresponding three-dimensional response surfaces.

Figure 2a represents a hypothetical relationship between supervisor-subordinate value similarity and organizational commitment (Chatman, 1991; Liedtka, 1989; Meglino, Ravlin, & Adkins, 1989, 1992; Reichers, 1986; Vancouver & Schmitt, 1991). The surface is concave and resembles a rising ridge, with its first principal axis running along the $Y = X$ line. The second principal axis crosses the first at the point $X = 10, Y = 10$ (representing the stationary point), well outside the range of the component measures. Overall, the surface depicts three basic effects. First, commitment is higher when supervisor and subordinate values are similar to one another than when they differ, as indicated by the downward slope of the surface on either side of the $Y = X$ line. Second, commitment is higher when supervisor and subordinate values are both high than when both are low, as shown by the positive slope along the $Y = X$ line. Third, in all cases in which supervisor and subordinate values match, a joint increase in value levels has a diminishing effect on commitment, as indicated by the slight downward curvature along the $Y = X$ line. Although studies of value similarity have typically not examined the latter two effects, they are theoretically plausible and can be directly tested with the methods described here.

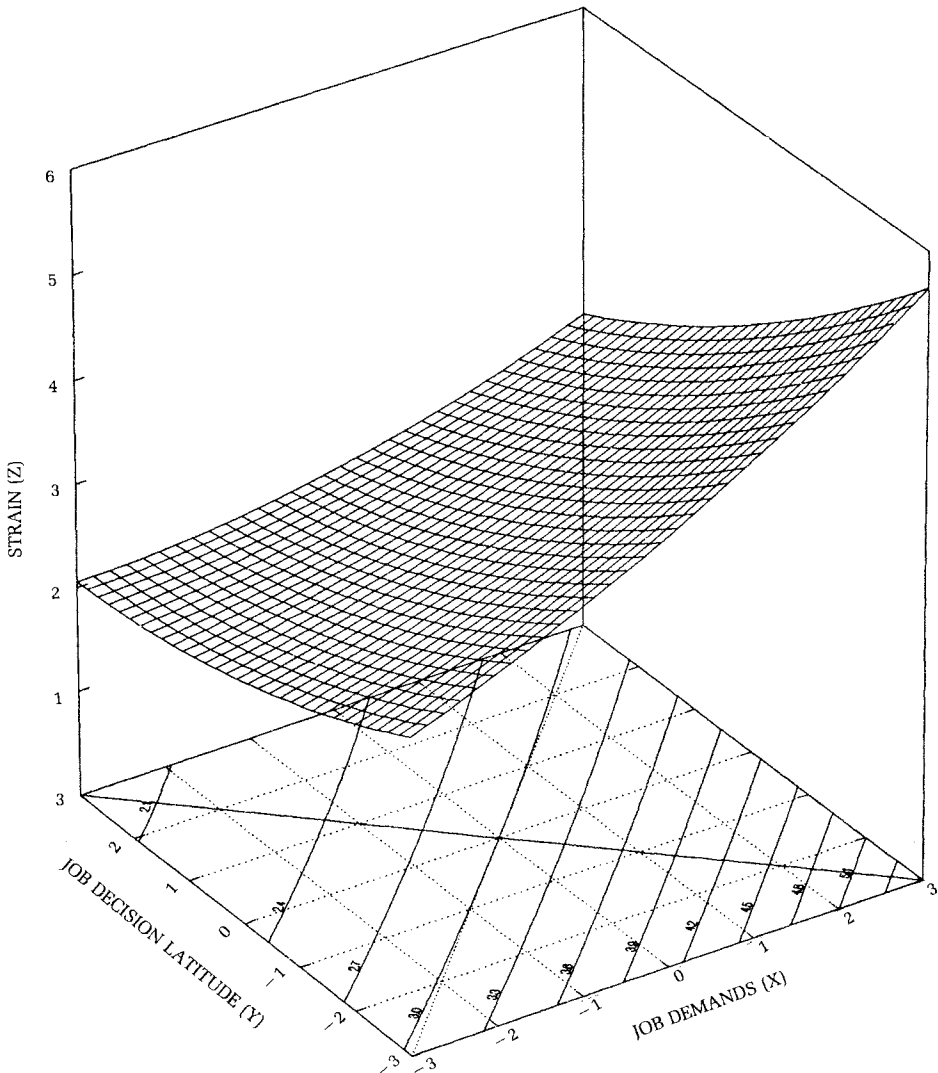
Figure 2b depicts a hypothetical relationship between job demands, job decision latitude, and strain (Karasek, 1979; Karasek & Theorell, 1990; Warr, 1990). The first principal axis runs along the $Y = -X$ line and intersects the second principal axis at the point $X = -3.16, Y = 3.16$, just beyond the left corner of the X, Y plane. As one moves away from the stationary point along

FIGURE 2a^a
Hypothetical Surface for Supervisor and Subordinate
Values Predicting Organizational Commitment
($Z = 5 + .1X + .1Y - .05X^2 + .09XY - .05Y^2$)



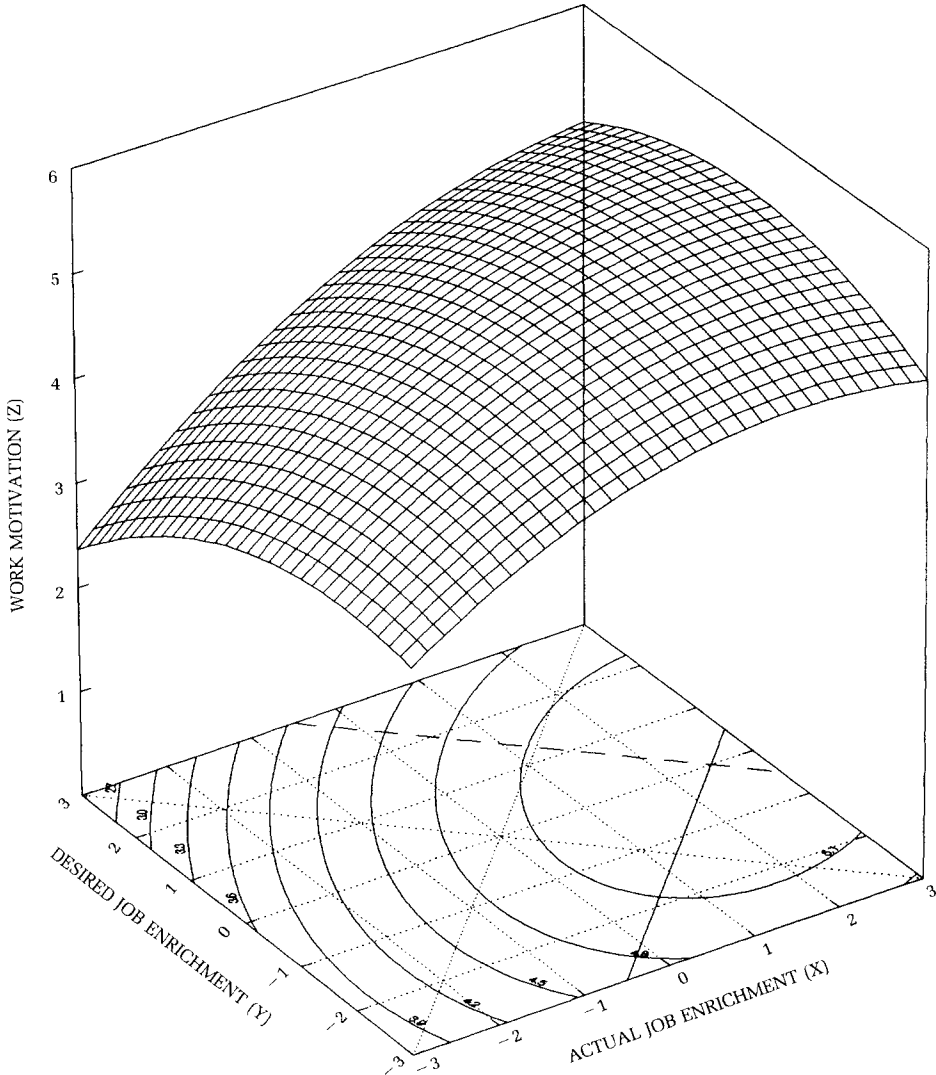
^a On the X,Y plane, the dotted line running diagonally from the near corner to the far corner represents the $Y = X$ line, and the dotted line running diagonally left to right represents the $Y = -X$ line. When the principal axes cross the X,Y plane within the range of the X and Y measure, the first principal axis is represented by a solid line and the second principal axis is represented by a dashed line.

FIGURE 2b^a
Hypothetical Surface for Job Demand and Job Decision Latitude
Predicting Strain ($Z = 3 + .3X - .3Y + .025X^2 - .045XY + .025Y^2$)



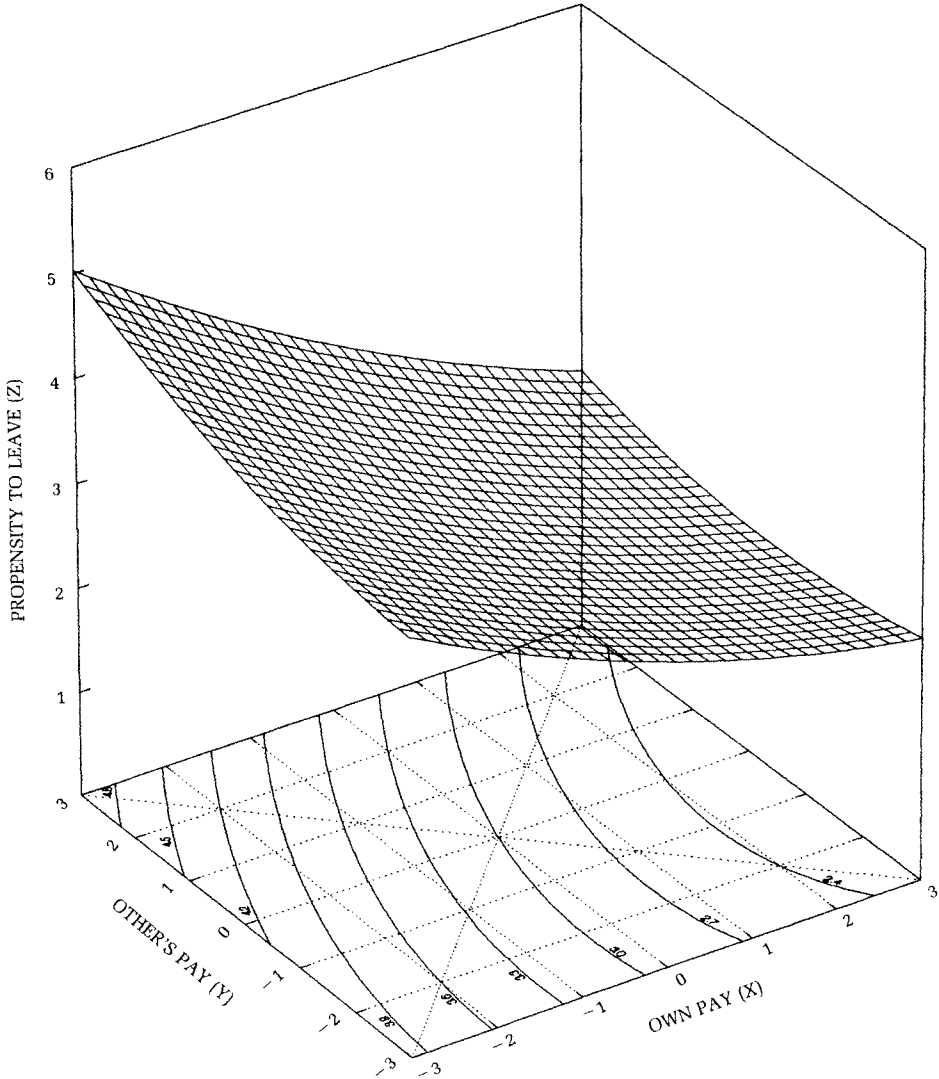
^a On the X,Y plane, the dotted line running diagonally from the near corner to the far corner represents the $Y = X$ line, and the dotted line running diagonally left to right represents the $Y = -X$ line. When the principal axes cross the X,Y plane within the range of the X and Y measure, the first principal axis is represented by a solid line and the second principal axis is represented by a dashed line.

FIGURE 2c^a
Hypothetical Surface for Actual and Desired Job Enrichment Predicting
Work Motivation ($Z = 5 + .3X - .1Y - .06X^2 + .04XY - .06Y^2$)



^a On the X,Y plane, the dotted line running diagonally from the near corner to the far corner represents the $Y = X$ line, and the dotted line running diagonally left to right represents the $Y = -X$ line. When the principal axes cross the X,Y plane within the range of the X and Y measure, the first principal axis is represented by a solid line and the second principal axis is represented by a dashed line.

FIGURE 2d^a
Hypothetical Surface for Pay Received by Self and Other Predicting
Propensity to Leave ($Z = 3 - .35X + .1Y + .025X^2 - .025XY + .025Y^2$)



^a On the X,Y plane, the dotted line running diagonally from the near corner to the far corner represents the $Y = X$ line, and the dotted line running diagonally left to right represents the $Y = -X$ line. When the principal axes cross the X,Y plane within the range of the X and Y measure, the first principal axis is represented by a solid line and the second principal axis is represented by a dashed line.

the first principal axis, the surface is positively sloped and somewhat convex. In essence, the surface indicates that strain is lowest when job demands are low and job decision latitude is high but increases at an increasing rate as job demands increase and job decision latitude decreases. The surface also indicates that strain is essentially constant when job demands match job decision latitude, as shown by the minimal slope along the $Y = X$ line.

Figure 2c shows a hypothetical relationship between actual job enrichment, desired job enrichment, and work motivation (Cherrington & England, 1980; Hackman & Oldham, 1980; Kulik, Oldham, & Hackman, 1987). The surface is concave and slightly elliptical, with its first principal axis running parallel to the $Y = X$ line but displaced to the right, into the region where X is greater than Y . The second principal axis intersects the first at the point $X = 2.5$, $Y = 0$, just inside the right edge of the X, Y plane. Overall, the surface indicates three effects. First, motivation increases as actual enrichment increases toward desired enrichment but begins to decrease when actual enrichment has moderately exceeded desired enrichment (in this case, by 2.5 units). Second, motivation is generally higher when actual and desired enrichment are high than when both are low. Third, when actual and desired enrichment are both high (in this case, about 1.25 units), motivation begins to decrease, suggesting that intense involvement may eventually lead to poor mental health, burnout, and other conditions deleterious to motivation (Kulik et al., 1987).

Finally, Figure 2d depicts the hypothetical effects of the pay received by oneself and a referent other on one's propensity to leave (Dittrich & Carrell, 1979; Oldham, Kulik, Ambrose, Stepina, & Brand, 1986; Scholl, Cooper, & McKenna, 1987; Summers & Hendrix, 1991; Telly, French, & Scott, 1971). The surface is convex, with its first principal axis running parallel to the $Y = -X$ line but intersecting the second principal axis at the point $X = 8$, $Y = 2$, well outside of the X, Y plane. As one moves along the $Y = X$ line, the surface is sloped downward and slightly convex. Overall, the surface indicates three effects. First, propensity to leave is notably greater for conditions of underpayment than for conditions of overpayment. Second, when the pay received by oneself and a referent other both increase equally, one's propensity to leave decreases. Third, as one moves up the pay scale, successively larger increases in pay received by both parties are required to produce a unit decrease in propensity to leave.

Ideally, the preceding examples would have been based on results from empirical studies of congruence that examined three-dimensional surfaces. Unfortunately, most studies of congruence have focused on two-dimensional relationships. That focus compelled us to derive plausible hypotheses from the literature to illustrate how relationships of interest in organizational research can be meaningfully depicted in terms of quadratic regression equations and their associated response surfaces. These surfaces show not only the effects of congruence between the component measures, but also other substantively meaningful effects, such as slope and curvature along the principal axes and the $Y = X$ line, shifts in surface maxima or

minima away from the $Y = X$ line, and so on. These examples also show that the location of the stationary point and principal axes and the slope of the surface along various lines of interest provide the core information necessary to interpret most surfaces. Fortunately, these features can be readily calculated from coefficients obtained from quadratic regression equations, as shown below.

Locating the Stationary Point and Principal Axes

Formulas expressing the stationary point and principal axes in terms of regression coefficients were derived from equations reported by Khuri and Cornell (1987). For a quadratic regression equation, the X, Y coordinates of the stationary point (X_0, Y_0) are:

$$X_0 = \frac{b_2b_4 - 2b_1b_5}{4b_3b_5 - b_4^2} \quad (7)$$

and

$$Y_0 = \frac{b_1b_4 - 2b_2b_3}{4b_3b_5 - b_4^2}. \quad (8)$$

Note that when the equality $4b_3b_5 = b_4^2$ holds, Equations 7 and 8 are undefined, meaning that the surface has no stationary point. This condition implies one of two types of surface, depending on the values of b_3 , b_4 , and b_5 . If any of these coefficients is nonzero, the surface is either a ridge with a constant slope along its first principal axis or a trough with a constant slope along its second principal axis. If b_3 , b_4 , and b_5 equal 0 simultaneously, the surface is a plane (e.g., Figure 1b). In this case, the interpretation of the surface is straightforward and does not require the framework described here.

The first and second principal axes can be expressed as lines in the X, Y plane. The equation for the first principal axis can be written as

$$Y = p_{10} + p_{11}X. \quad (9)$$

The equation for p_{11} is

$$p_{11} = \frac{b_5 - b_3 + \sqrt{(b_3 - b_5)^2 + b_4^2}}{b_4}. \quad (10)$$

Two properties of Equation 10 are worth noting. First, when b_3 and b_5 are equal (as implied by the squared difference), Equation 10 reduces to $|b_4|/b_4$. In this case, p_{11} equals either 1 or -1 , depending upon whether the sign of b_4 is positive or negative. Second, when b_4 equals 0, both the numerator and denominator of Equation 10 become 0, rendering it undefined. In that case, one of three implications regarding the first principal axis of the surface pertains: if b_3 is greater than b_5 , the first principal axis has a slope of 0 and runs parallel to the x -axis. If b_3 is less than b_5 , the first principal axis has a

slope of infinity and runs parallel to the y -axis. Finally, if b_3 and b_5 are equal, the surface is a symmetric bowl or cap (depending on whether b_3 and b_5 are positive or negative), and no unique set of axes can be identified.

Once X_0 , Y_0 , and p_{11} have been calculated, p_{10} can be calculated using the following formula:

$$p_{10} = Y_0 - p_{11}X_0. \quad (11)$$

Note that if p_{11} equals 0, p_{10} equals Y_0 , indicating that the first principal axis runs parallel to the x -axis and intersects the y -axis at the point Y_0 .

The equation for the second principal axis can be written as

$$Y = p_{20} + p_{21}X. \quad (12)$$

The equation for p_{21} is

$$p_{21} = \frac{b_5 - b_3 - \sqrt{(b_3 - b_5)^2 + b_4^2}}{b_4}. \quad (13)$$

Note that the equation for p_{21} is identical to that for p_{11} , except that the sign preceding the expression the expression $\sqrt{(b_3 - b_5)^2 + b_4^2}$ is reversed. Hence, when b_3 and b_5 are equal, Equation 13 becomes equivalent to $-|b_4|/b_4$. Consequently, if b_4 is positive, p_{21} equals -1 , whereas if b_4 is negative, p_{21} equals 1 . Analogously, if b_4 equals 0 and b_3 is greater than b_5 , the slope of the second principal axis is infinity, whereas if b_4 equals 0 and b_3 is less than b_5 , the slope of the second principal axis is 0. As before, if b_4 equals 0 and b_3 and b_5 are equal, the surface has no unique set of principal axes.

Once X_0 , Y_0 , and p_{21} have been calculated, p_{20} can be calculated as follows:

$$p_{20} = Y_0 - p_{21}X_0. \quad (14)$$

The preceding equations can be used to locate the principal axes in reference to the x - and y -axes. However, other information regarding the location of the principal axes may also be relevant. For example, congruence researchers often hypothesize that some outcome, such as job satisfaction or company performance, is maximized at the point of "perfect fit" (e.g., Drazin & Van de Ven, 1985; Rice et al., 1989). This hypothesis implies a ridge with its first principal axis running along the $Y = X$ line, meaning that $p_{10} = 0$ and $p_{11} = 1$. If p_{11} differs from 1, the surface is rotated off the $Y = X$ line. If the quantity $-p_{10}/(1 + p_{11})$ differs from 0, the surface is shifted laterally along the $Y = -X$ line, with its first principal axis intersecting that line at the point $X = -p_{10}/(1 + p_{11})$, $Y = p_{10}/(1 + p_{11})$. In either case, the hypothesis that the first principal axis runs along the $Y = X$ line is rejected.

Congruence researchers also hypothesize that certain outcomes, such as psychological strain and turnover, are minimized at the point of perfect fit (e.g., Dittrich & Carrell, 1979; French et al., 1982). This hypothesis implies a trough with its second principal axis running along the $Y = X$ line (Figure

1d), meaning that $p_{20} = 0$ and $p_{21} = 1$. As before, if p_{21} differs from 1, the surface is rotated off the $Y = X$ line, whereas if the quantity $-p_{20}/(1 + p_{21})$ differs from 0, the surface is shifted laterally along the $Y = -X$ line, with its second principal axis intersecting that line at the point $X = -p_{20}/(1 + p_{21})$, $Y = p_{20}/(1 + p_{21})$. Again, either result would indicate that the second principal axis deviates from the $Y = X$ line.

Calculating Slopes Along Lines of Interest

The slope of the surface along a given line in the X, Y plane can be calculated by substituting the expression for that line into Equation 6. For example, most congruence hypotheses incorporate the assumption that the slope of the surface along the $Y = X$ line is 0, meaning that Z is the same at all points along the line of perfect fit. The expression for this line in the X, Y plane is simply $Y = X$. Substituting X for Y in Equation 6 yields the following:

$$\begin{aligned} Z &= b_0 + b_1X + b_2X + b_3X^2 + b_4X^2 + b_5X^2 + e \\ &= b_0 + (b_1 + b_2)X + (b_3 + b_4 + b_5)X^2 + e. \end{aligned} \quad (15)$$

As Equation 15 shows, the slope along the $Y = X$ line at the point $X = 0$ (and, by construction, $Y = 0$) is given by the sum of b_1 and b_2 , and the curvature along that line is given by the sum of b_3 , b_4 , and b_5 . If either of these sums differs significantly from 0, the hypothesis that the surface is flat along the $Y = X$ line is rejected.

Studies of congruence are also often concerned with the slope of the surface along the $Y = -X$ line (running perpendicular to the $Y = X$ line). For example, hypotheses derived from P-E fit theory often state that strain increases on either side of the point of perfect fit (e.g., French et al., 1982). Such hypotheses imply a parabolic surface that is U-shaped along the $Y = -X$ line, with its turning point at $Y = X$. The slope of the surface along that line can be calculated by substituting $-X$ for Y in Equation 6:

$$\begin{aligned} Z &= b_0 + b_1X - b_2X + b_3X^2 - b_4X^2 + b_5X^2 + e \\ &= b_0 + (b_1 - b_2)X + (b_3 - b_4 + b_5)X^2 + e. \end{aligned} \quad (16)$$

If the quantity $(b_3 - b_4 + b_5)$ is greater than 0, the surface is curved upward along the $Y = -X$ line, and if the quantity $(b_1 - b_2)$ equals 0, the surface is flat at the point $X = 0$, $Y = 0$ (the origin of the x - and y -axes). Taken together, these results would indicate the hypothesized slope along the $Y = -X$ line.

Slopes along the principal axes are calculated in a similar manner. For example, the slope along the first principal axis can be determined by substituting $p_{10} + p_{11}X$ for Y in Equation 6:

$$\begin{aligned} Z &= b_0 + b_1X + b_2(p_{10} + p_{11}X) + b_3X^2 + b_4X(p_{10} + p_{11}X) \\ &\quad + b_5(p_{10} + p_{11}X)^2 + e \\ &= b_0 + b_2p_{10} + b_5p_{10}^2 + (b_1 + b_2p_{11} + b_4p_{10} + 2b_5p_{10}p_{11})X \\ &\quad + (b_3 + b_4p_{11} + b_5p_{11}^2)X^2 + e. \end{aligned} \quad (17)$$

As Equation 17 shows, the slope at the point where $X = 0$ (that is, where the first principal axis crosses the y-axis) is given by the quantity $(b_1 + b_2p_{11} + b_4p_{10} + 2b_5p_{10}p_{11})$, and the curvature is given by $(b_3 + b_4p_{11} + b_5p_{11}^2)$. The slope along the second principal axis can be calculated by replacing p_{10} and p_{11} with p_{20} and p_{21} , respectively, in Equation 17, which yields the following:

$$\begin{aligned} Z &= b_0 + b_1X + b_2(p_{20} + p_{21}X) + b_3X^2 + b_4X(p_{20} + p_{21}X) \\ &\quad + b_5(p_{20} + p_{21}X)^2 + e \\ &= b_0 + b_2p_{20} + b_5p_{20}^2 + (b_1 + b_2p_{21} + b_4p_{20} + 2b_5p_{20}p_{21})X \\ &\quad + (b_3 + b_4p_{21} + b_5p_{21}^2)X^2 + e. \end{aligned} \quad (18)$$

Tests of Significance

Tests of significance for expressions involving linear combinations of regression coefficients, such as those preceding X and X^2 in Equations 15 and 16, can be readily conducted because the standard errors for these expressions can be derived using ordinary rules for calculating the variance of a linear combination of random variables (e.g., DeGroot, 1975; Neter, Wasserman, & Kutner, 1989). However, expressions involving products and ratios of regression coefficients, such as formulas for the stationary point, principal axes, and slopes along the principal axes, cannot be tested using conventional procedures because formulas for the standard errors of these expressions are not generally available (Peddada, 1992).

When the formula for the standard error of an expression is unavailable, nonparametric procedures, such as the jackknife and bootstrap, are applicable (Efron, 1982; Efron & Gong, 1983; Tukey, 1958). For this article, we used the jackknife for its computational ease and demonstrated ability to approximate known standard errors (Efron & Gong, 1983; Peddada, 1992). The procedure used to compute standard errors using the jackknife is described in the Appendix.

AN EMPIRICAL EXAMPLE

To illustrate the framework described here, we used data from the classic person-environment fit study conducted by French and colleagues (1982) and reanalyzed by Edwards and Harrison (1993). Regression coefficients from the six equations reported in Table 1 were used to calculate the stationary points, principal axes, and slopes along four lines, including $Y = X$, $Y = -X$, and the first and second principal axes. We tested the slopes along the $Y = X$ and $Y = -X$ lines using standard procedures for linear combinations of regression coefficients (Neter et al., 1989) and tested the slopes along the principal axes and the locations of the stationary points and principal axes using the jackknife procedure. Tables 2 and 3 present results of these analyses, and Figures 3a–3f show plots of all six surfaces (for job complexity, we reversed the scaling of the x- and y-axes to permit a better view of the surfaces).

To interpret the results for each surface, we proceeded as follows. First,

TABLE 2
Stationary Points and Principal Axes^a

Job Dimension	Outcome	Stationary Point		First Principal Axis		Second Principal Axis	
		X ₀	Y ₀	P ₁₀	P ₁₁	P ₂₀	P ₂₁
Job complexity	Job dissatisfaction	-3.272	-4.356	-6.804	-0.748**	0.018	1.337**
Job complexity	Work load dissatisfaction	-1.832	-3.258	-4.067	-0.442**	0.890*	2.264** ^{b,c}
Job complexity	Boredom	3.592**	3.090**	6.196**	-0.865**	-1.064	1.157**
Job complexity	Depression	-0.343	-0.191	-0.408	-0.633**	0.350	1.580**
Job complexity	Anxiety	0.466	0.916**	1.372*	-0.980**	0.440	1.021**
Quantitative work load	Work load dissatisfaction	-0.785*	-0.634	-0.905	-0.345**	1.641**	2.900** ^{b,c}

^a N ranged from 617 to 625. For columns labeled X₀ and Y₀, table entries are coordinates of the stationary point in the X, Y plane. For columns labeled P₁₀ and P₁₁, table entries are the intercept and slope of the first principal axis in the X, Y plane; and for columns labeled P₂₀ and P₂₁, table entries are the intercept and slope of the second principal axis in the X, Y plane. Standard errors for all values were estimated using the jackknife procedure described in the Appendix.

^b For this surface, the slope of the second principal axis (P₂₁) differed significantly from 1 (p < .05).

^c For this surface, the quantity -P₂₀/(1 + P₂₁) was significantly less than 0 (p < .05), indicating a lateral shift of the second principal axis along the Y = -X line into the region where X is less than Y.

* p < .05

** p < .01

TABLE 3
Slopes Along Lines of Interest^a

Job Dimension	Y = X		Y = -X		First Principal Axis		Second Principal Axis	
	α_x	α_{x^2}	α_x	α_{x^2}	α_x	α_{x^2}	α_x	α_{x^2}
Job complexity	-0.198**	-0.017	0.035	0.416**			-0.238**	-0.036
Job complexity	-0.123*	0.029	0.329**	0.442**	-1.118	0.258**	-0.498	-0.136
Job complexity	-0.490**	0.071*	-0.444**	0.484**			-0.578**	0.080*
Job complexity	-0.006	-0.024	0.051	0.173**	0.088	0.128*	-0.042	-0.061
Job complexity	0.088*	-0.062**	0.105	0.244**	-0.223	0.239*	0.059	-0.064**
Quantitative work load	-0.078	-0.109	0.831**	0.693**	0.827*	0.527**	-2.652	-1.690

^a N ranged from 617 to 625. For each line, α_x represents the computed coefficient on X, and α_{x^2} represents the computed coefficient on X². For example, for the Y = X line, α_x represents ($b_1 + b_2$) and α_{x^2} represents ($b_3 + b_4 + b_5$) (see Equation 17). We derived standard errors for slopes along the Y = X and Y = -X lines using standard rules for the variance of a linear combination of random variables and calculated standard errors for slopes along the principal axes using the jackknife procedure described in the Appendix. The slope along a principal axis is not reported when the axis does not cross the X,Y plane in the range of the component measures.

* p < .05

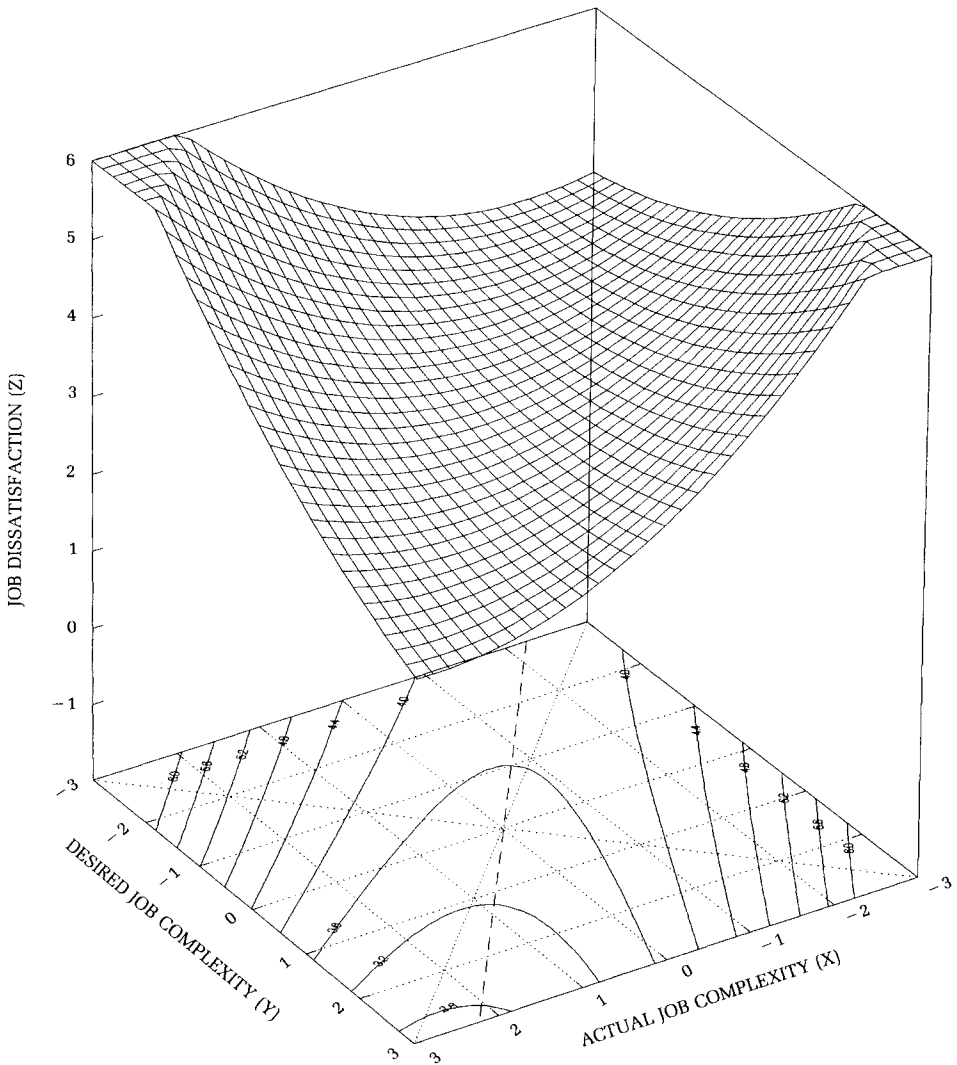
** p < .01

we examined the coordinates of the stationary point to determine whether the surface was centered at the origin of the x - and y -axes (that is, the point $X = 0, Y = 0$). Next, we examined the intercepts and slopes of the principal axes of the surface. Tests of whether the slopes of the principal axes differed from 0 were supplemented by tests of whether the slope of the second principal axis (p_{21}) differed from 1 and whether the second principal axis was shifted laterally along the $Y = -X$ line, as indicated by the quantity $-p_{20}/(1 + p_{21})$. We conducted these additional tests because P-E fit theory states that strain is minimized when actual and desired amounts of job attributes are equal (French et al., 1982), implying a U-shaped surface with its second principal axis (the region of minimum strain) running along the $Y = X$ line (Figure 1d). Third, we examined the slope of the surface along the $Y = X$ and $Y = -X$ lines. Slopes along the principal axes were also considered when the principal axes differed from the $Y = X$ and $Y = -X$ lines but still passed through the X, Y plane within the range of the X and Y measures. Although this procedure emphasized only a subset of the results reported in Tables 2 and 3, the remaining results can be examined to obtain a more complete understanding of each surface.

The surface for actual and desired job complexity predicting job dissatisfaction (Figure 3a) was saddle-shaped, with its stationary point located at $X = -3.272, Y = -4.356$, just beyond the far-back corner of the X, Y plane. The first principal axis did not cross within the range of the component measures, but the second principal axis passed almost exactly through the origin of the x - and y -axes, at the center of the X, Y plane. The slope of the second principal axis was slightly greater than 1 ($p_{21} = 1.337$), indicating a modest but nonsignificant counterclockwise rotation of the surface off the $Y = X$ line. Along the $Y = -X$ line, the surface was convex ($a_{x^2} = 0.416, p < .01$) but was flat at the origin ($a_x = 0.035, n.s.$). Taken together, these results indicated that, for a given level of actual job complexity, job dissatisfaction was minimized when actual and desired job complexity were equal and increased in either direction. Further analyses showed that the slope of the surface along the $Y = X$ line was negative and linear ($a_x = -0.198, p < .01$; $a_{x^2} = -0.017, n.s.$; see Table 3), thereby indicating that job dissatisfaction was lower when actual and desired job complexity were both high than when both were low.

The surface for actual and desired job complexity predicting work load dissatisfaction (Figure 3b) was also saddle-shaped, with its stationary point at $X = -1.832$ and $Y = -3.258$, just beyond the back edge of the X, Y plane. The slope of the second principal axis was significantly greater than 1 ($p_{21} = 2.264, p < .01$), indicating a counterclockwise rotation off the $Y = X$ line. In addition, the quantity $-p_{20}/(1 + p_{21})$ was significant and negative ($-0.273, p < .05$), indicating a modest lateral shift along the $Y = -X$ line into the region where X is less than Y . The slope of the surface along the $Y = X$ line was negative and essentially linear ($a_x = -0.123, p < .05$; $a_{x^2} = 0.029, n.s.$), whereas the slope along the $Y = -X$ line was convex ($a_{x^2} = 0.442, p < .01$) and positive at the origin ($a_x = 0.329, p < .01$). In contrast,

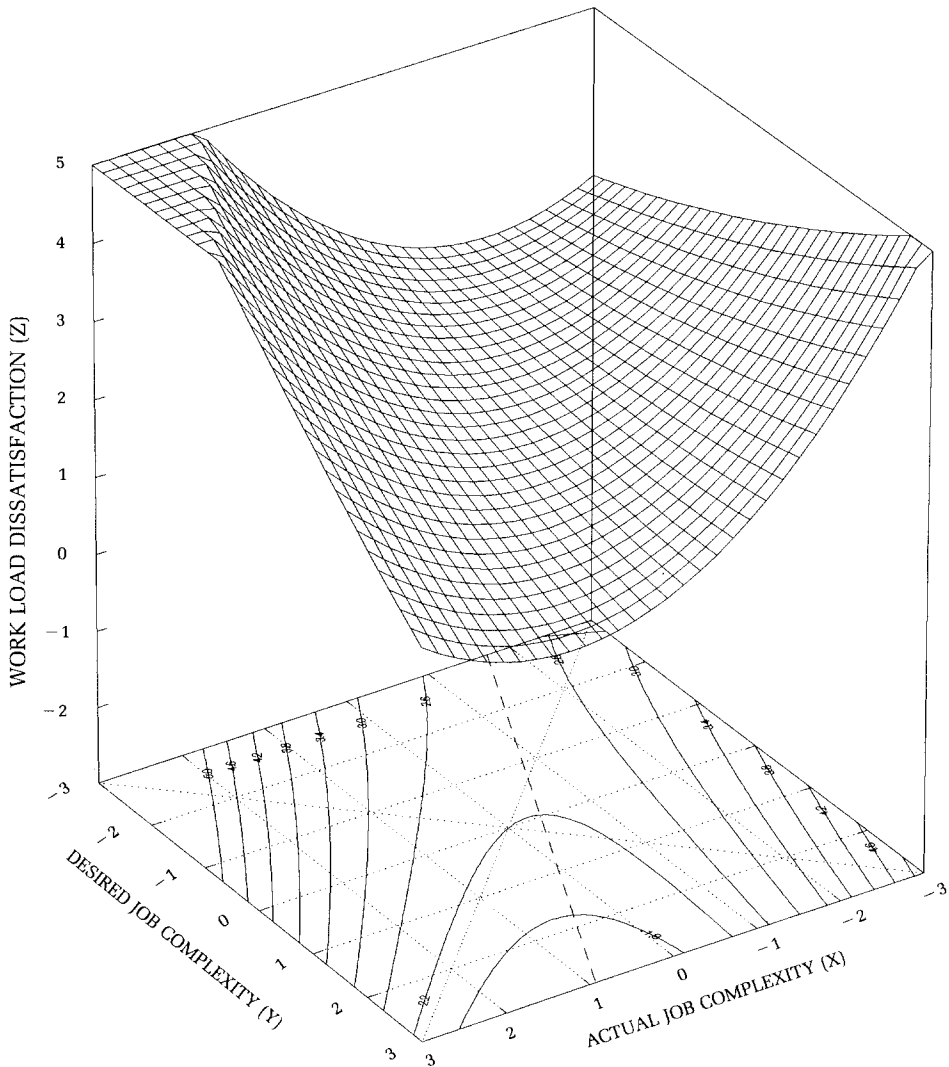
FIGURE 3a
Job Complexity Predicting Job Dissatisfaction^a



^a On the X,Y plane, the dotted line running diagonally from the near corner to the far corner represents the $Y = X$ line, and the dotted line running diagonally left to right represents the $Y = -X$ line. When the principal axes cross the X,Y plane within the range of the X and Y measures, the first principal axis is represented by a solid line and the second principal axis is represented by a dashed line.

the slope along the second principal axis was not significant ($\alpha_x = -0.498$, $\alpha_{x^2} = -0.136$, both n.s.). Taken together, these results indicate a surface much like that for job dissatisfaction, with two exceptions. First, when actual and desired job complexity were both low, work load dissatisfaction

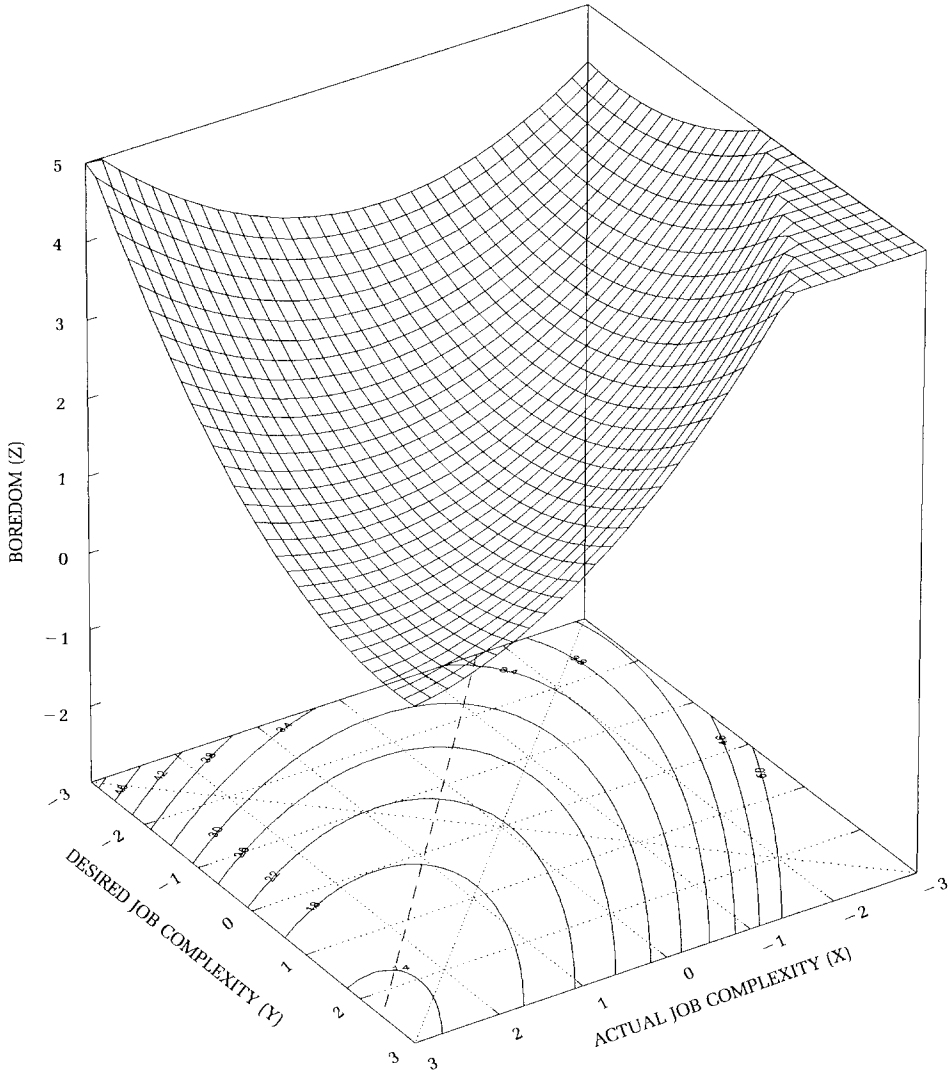
FIGURE 3b
Job Complexity Predicting Work Load Dissatisfaction^a



^a On the X,Y plane, the dotted line running diagonally from the near corner to the far corner represents the $Y = X$ line, and the dotted line running diagonally left to right represents the $Y = -X$ line. When the principal axes cross the X,Y plane within the range of the X and Y measures, the first principal axis is represented by a solid line and the second principal axis is represented by a dashed line.

was lowest when actual job complexity exceeded desired job complexity; but when actual and desired job complexity were both high, work load dissatisfaction was lowest when actual job complexity fell short of desired job complexity. Second, work load dissatisfaction was somewhat greater

FIGURE 3c
Job Complexity Predicting Boredom^a

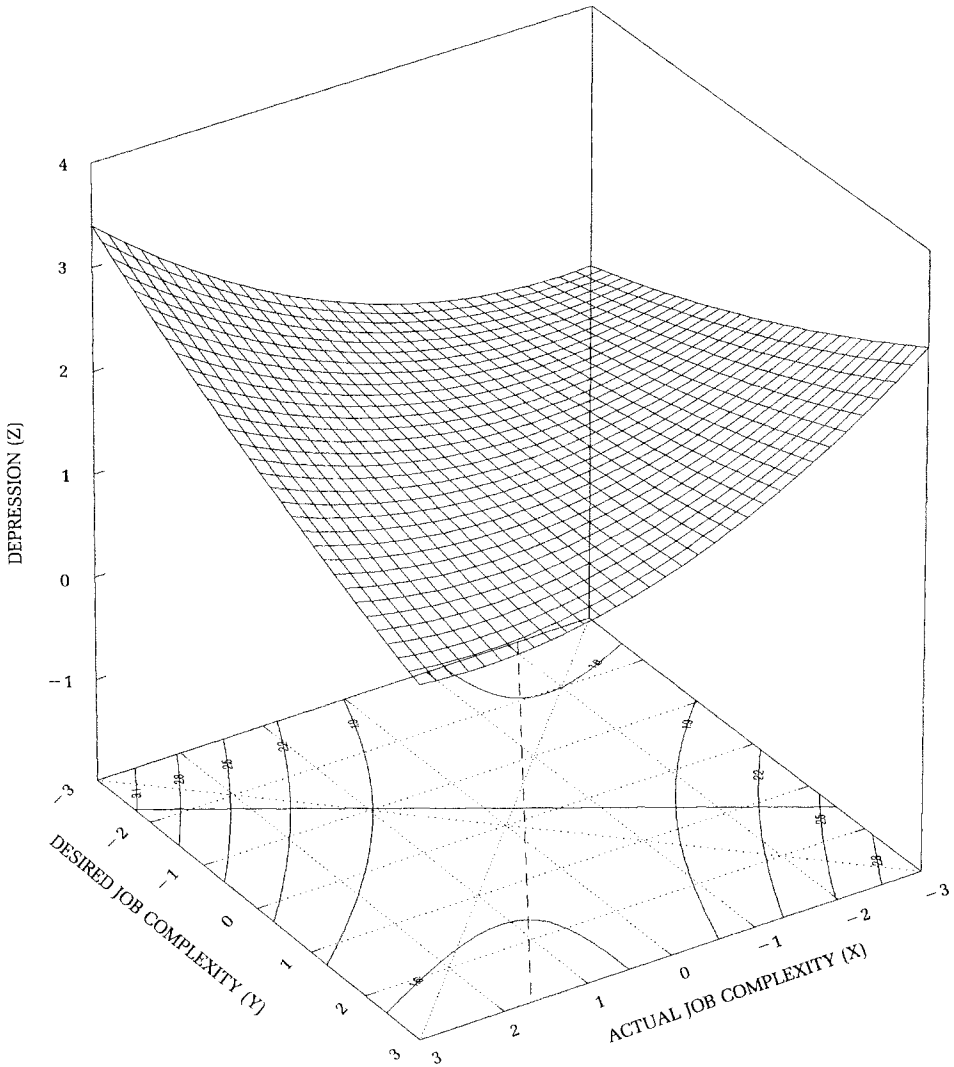


^a On the X,Y plane, the dotted line running diagonally from the near corner to the far corner represents the $Y = X$ line, and the dotted line running diagonally left to right represents the $Y = -X$ line. When the principal axes cross the X,Y plane within the range of the X and Y measures, the first principal axis is represented by a solid line and the second principal axis is represented by a dashed line.

when actual job complexity exceeded desired job complexity than when it fell short of desired job complexity.

The surface for actual and desired job complexity predicting boredom (Figure 3c) was convex, with its stationary point at $X = 3.592$, $Y = 3.090$,

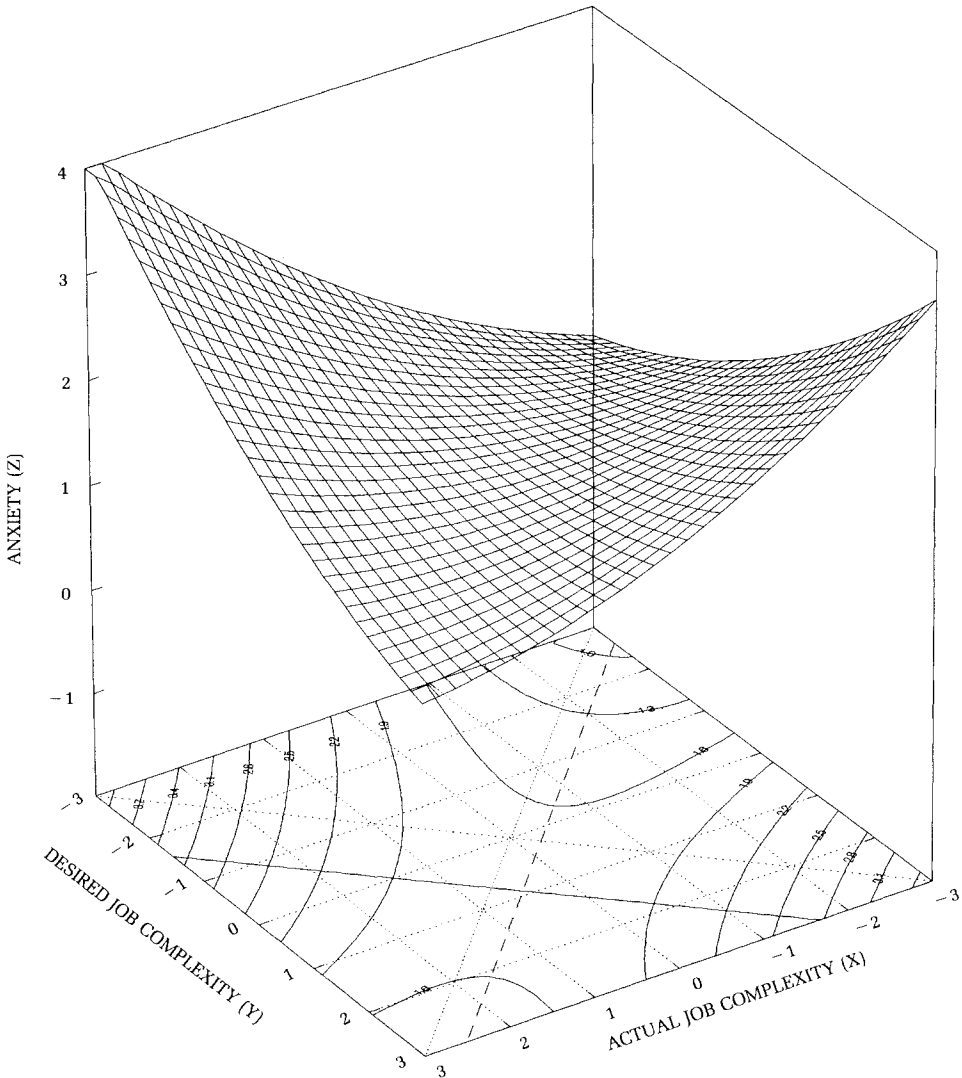
FIGURE 3d
Job Complexity Predicting Depression^a



^a On the X,Y plane, the dotted line running diagonally from the near corner to the far corner represents the $Y = X$ line, and the dotted line running diagonally left to right represents the $Y = -X$ line. When the principal axes cross the X,Y plane within the range of the X and Y measures, the first principal axis is represented by a solid line and the second principal axis is represented by a dashed line.

just outside the near corner of the X,Y plane. The slope of the second principal axis was 1.157, representing a slight but nonsignificant rotation from the $Y = X$ line. The slope along the $Y = X$ line was slightly convex ($a_{x^2} = 0.071, p < .05$) and negative at the origin ($a_x = -0.490, p < .01$), whereas the

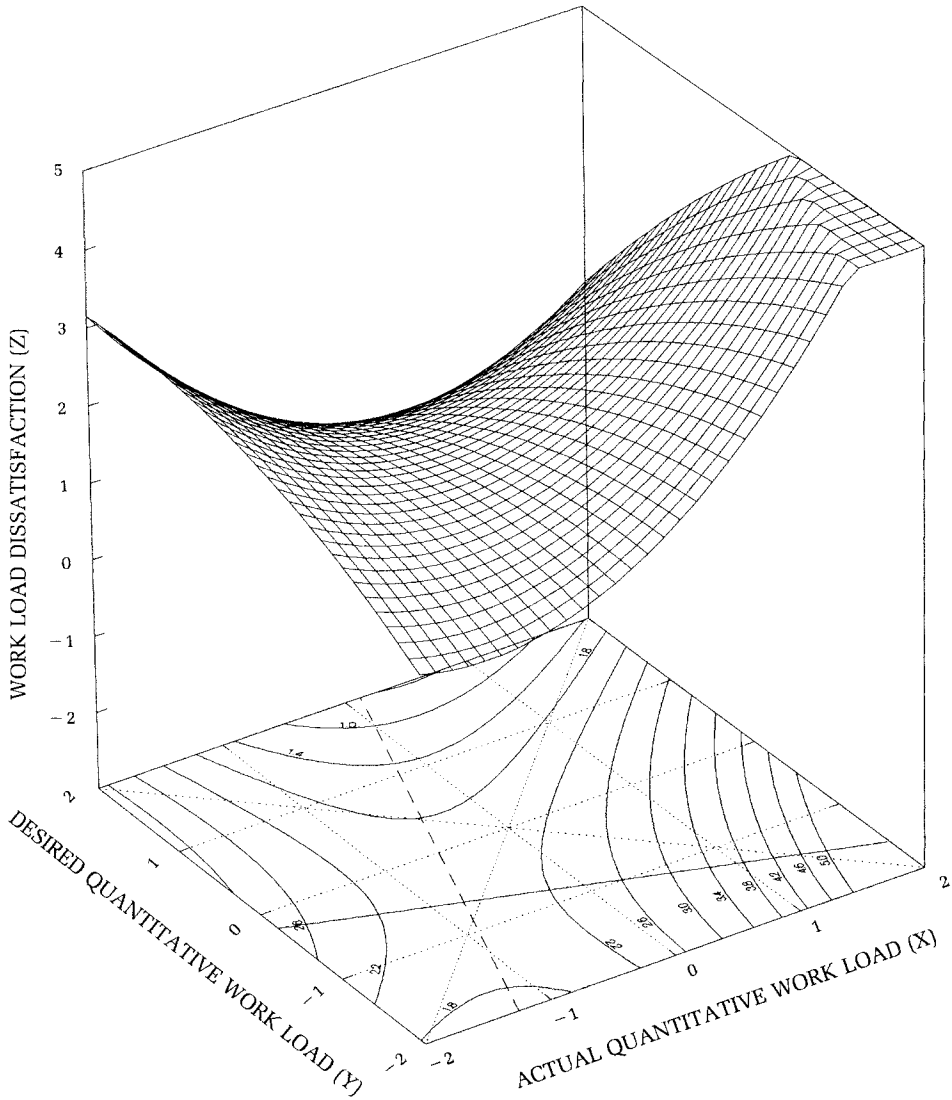
FIGURE 3e
Job Complexity Predicting Anxiety^a



^a On the X,Y plane, the dotted line running diagonally from the near corner to the far corner represents the $Y = X$ line, and the dotted line running diagonally left to right represents the $Y = -X$ line. When the principal axes cross the X,Y plane within the range of the X and Y measures, the first principal axis is represented by a solid line and the second principal axis is represented by a dashed line.

slope along the $Y = -X$ line was more notably convex ($a_{x^2} = 0.484, p < .01$), with a moderate negative slope at the origin ($a_x = -0.444, p < .01$). Taken together, these results indicated that boredom increased as actual job complexity deviated from desired job complexity and that boredom was lower

FIGURE 3f
Quantitative Work Load Predicting Work Load Dissatisfaction^a



^a On the X,Y plane, the dotted line running diagonally from the near corner to the far corner represents the $Y = X$ line, and the dotted line running diagonally left to right represents the $Y = -X$ line. When the principal axes cross the X,Y plane within the range of the X and Y measures, the first principal axis is represented by a solid line and the second principal axis is represented by a dashed line.

when actual and desired job complexity were both high than when both were low. The slight upward curvature along the $Y = X$ line also indicated that, as actual and desired job complexity both decreased, boredom increased at an increasing rate.

The surface for actual and desired job complexity predicting depression (Figure 3d) was saddle-shaped, with its stationary point at $X = -0.343$, $Y = -0.191$, near the origin of the x - and y -axes. The slope of the first and second principal axes did not differ from -1 and 1 , respectively ($p_{11} = -0.633$, $p_{21} = 1.580$), indicating no appreciable rotation off the $Y = -X$ and $Y = X$ lines. The surface was flat along the $Y = X$ line ($\alpha_x = -0.006$, $\alpha_{x^2} = -0.024$, both n.s.) and convex along the $Y = -X$ line ($\alpha_x = 0.051$, n.s., $\alpha_{x^2} = 0.173$, $p < .01$). Overall, these results essentially indicated that depression increased as actual job complexity deviated from desired job complexity. This finding is corroborated by the difference in the R^2 between the constrained and unconstrained equations reported in Table 1, which, although statistically significant, was relatively small (.017).

The surface for actual and desired job complexity predicting anxiety (Figure 3e) was also saddle-shaped, with its stationary point at $X = 0.466$, $Y = 0.916$, shifted somewhat from the origin along the y -axis. The slopes of the first and second principal axes (p_{11} and p_{21}) were -0.980 and 1.021 , respectively, corresponding very closely to -1 and 1 . However, the intercept of the first principal axis differed from 0 ($p_{10} = 1.372$, $p < .05$), a finding that, combined with the location of Y_0 , indicated a lateral shift along the y -axis. The surface was convex along the first principal axis ($\alpha_{x^2} = 0.239$, $p < .01$) but essentially flat where it crossed the y -axis ($\alpha_x = -0.223$, n.s.). In contrast, the surface was slightly concave along the $Y = X$ line ($\alpha_{x^2} = -0.062$, $p < .01$), with a modest positive slope where it crossed the y -axis ($\alpha_x = 0.088$, $p < .05$). These results indicated that anxiety increased as actual job complexity deviated from desired job complexity and also that anxiety was higher when actual and desired job complexity were both moderate (in this case, about .7 units) than when they were both either high or low.

Finally, the surface for actual and desired quantitative work load predicting work load dissatisfaction (Figure 3f) was saddle-shaped, with its stationary point at $X = -0.785$, $Y = -0.634$, shifted slightly downward along the $Y = X$ line. The slopes of the first and second principal axes (p_{11} and p_{21}) were -0.345 and 2.900 , respectively, indicating a marked counterclockwise rotation. In addition, the quantity $-p_{20}/(1 + p_{21})$ was significant and negative (-0.421 , $p < .05$) indicating a lateral shift along the $Y = -X$ line into the region where X is less than Y . The surface was convex along the first principal axis ($\alpha_{x^2} = 0.527$, $p < .01$) and positively sloped where it crossed the y -axis ($\alpha_x = 0.827$, $p < .05$). In contrast, the surface was concave along the second principal axis and negatively sloped where it crossed the y -axis, but neither α_x nor α_{x^2} was significant, due to the sizable jackknife estimates of their standard errors. Essentially, these results indicated that, when actual and desired work load were below their scale midpoints, work load dissatisfaction increased as actual work load deviated from desired work load, but when actual and desired work load were above their scale midpoints, work load dissatisfaction was lowest when actual work load was somewhat less than desired work load. In addition, work load dissatisfaction

was higher when actual work load exceeded desired work load than when it fell short of desired work load.

DISCUSSION

This article presents a general framework for testing and interpreting quadratic regression equations within the study of congruence in organizational research. These equations avoid many problems with difference scores but permit direct tests of conceptual models difference scores are intended to represent (Edwards, in press). Unfortunately, these equations often yield patterns of coefficients that are difficult to interpret, particularly when models specified a priori are not supported. The framework presented here shows how coefficients from quadratic regression equations can be used to comprehensively describe and test the surfaces they imply. Thus, this framework clarifies the interpretation of quadratic regression equations and permits rigorous evaluation of conceptual models relevant to the study of congruence, including models that are substantially more complex than those represented by difference scores.

The incremental contribution of the framework presented here may be seen by comparing our results to those reported by French and colleagues (1982; see also Caplan et al., 1980), who analyzed the relationship between P-E fit and strain using various transformations of algebraic and squared difference scores. French and colleagues concluded that the functional form relating actual and desired job complexity to the five indexes of strain reported in Table 1 was essentially U-shaped. They elaborated this general conclusion by stating that too little job complexity exhibited a stronger relationship with boredom, whereas too much job complexity exhibited stronger relationships with work load dissatisfaction, depression, and anxiety. French and colleagues also reported that the functional form relating actual and desired quantitative work load to work load dissatisfaction was U-shaped, with stronger effects for excess work load.

Subsequent reanalyses by Edwards and Harrison (1993) using the polynomial regression procedure (Edwards, in press) indicated that, with few exceptions, the constraints imposed by the difference scores used by French and colleagues were rejected. Plots of the surfaces corresponding to the equations reported in Table 1 suggested various deviations from the surface indicated by the squared difference (Figure 1d), such as slopes along the $Y = X$ line, lateral shifts, and counterclockwise rotations. However, Edwards and Harrison were forced to base their conclusions primarily on visual inspection of these surfaces because the framework presented here was unavailable.

By applying this framework, we can now draw firm conclusions regarding the surfaces corresponding to the equations reported in Table 1. For example, consistent with the findings reported by French and colleagues (1982), all six surfaces were U-shaped, evidenced by the significant, positive coefficients on α_{x^2} along the $Y = -X$ line (or, for rotated surfaces, along the first principal axis). Furthermore, excess job complexity and quantitative

work load exacerbated work load dissatisfaction, as shown by the lateral shifts in these surfaces along the $Y = -X$ line, into the region where X is less than Y . However, contrary to French and colleagues' findings, the functions relating actual and desired job complexity to boredom, depression, and anxiety were essentially symmetric. This is shown by the locations of the second principal axes of these surfaces, which did not deviate from the $Y = X$ line (p_{21} and the quantity $-p_{20}/(1 + p_{21})$ did not differ significantly from 1 and 0, respectively). In addition, the surfaces relating job complexity and quantitative work load to work load dissatisfaction were rotated counterclockwise, indicating that, when actual and desired amounts of these job dimensions were low, a slight excess minimized work load dissatisfaction, whereas when actual and desired amounts were high, a slight deficiency minimized work load dissatisfaction. Furthermore, several surfaces were sloped along the line of perfect fit (the $Y = X$ line), including a positive slope for actual and desired job complexity predicting anxiety and negative slopes for actual and desired job complexity predicting job dissatisfaction, work load dissatisfaction, and boredom. These additional findings, although not reported by French and colleagues, are nonetheless consistent with P-E fit theory, which suggest that strain may vary along the $Y = X$ line and be minimized at points other than perfect fit (Caplan, 1983; French et al., 1982; Harrison, 1978, 1985). By applying the framework presented here in other studies of congruence, researchers are likely to find theoretically relevant effects that have previously gone undetected.

The framework presented here was illustrated using paired measures of individual-level constructs. This framework can, however, be readily applied to other forms of congruence research. For example, numerous studies have examined congruence between organization-level constructs, such as technology and structure (Alexander & Randolph, 1985; Dewar & Werbel, 1979; Fry & Slocum, 1984), an organization and its environment (Anderson & Zeithaml, 1984; Miller, 1991), and actual and ideal scores on measures of organizational strategy (Venkatraman, 1990; Venkatraman & Prescott, 1990) or structure (Drazin & Van de Ven, 1985; Gresov, 1989). Naturally, the effects of congruence between these constructs can be readily examined using the framework described here, because this framework is applicable to measures of any paired constructs of interest in congruence research.

Furthermore, many studies have examined the effects of congruence along multiple dimensions, usually expressed in terms of a profile similarity index (e.g., Drazin & Van de Ven, 1985; Gresov, 1989; Rounds et al., 1987; Sparrow, 1989; Turban & Jones, 1988; Venkatraman, 1990; Venkatraman & Prescott, 1990; Zalesny & Kirsch, 1989). Unfortunately, using profile similarity indexes to represent congruence introduces numerous methodological problems (Cronbach, 1958; Edwards, in press; Johns, 1981; Lykken, 1956; Nunnally, 1962). Many of these problems can be avoided by examining congruence not between entire profiles, but between specific, paired dimensions, using quadratic regression equations to depict the hypothesized relationship (Cronbach, 1958; Edwards, 1993). If separate equations are used for each pair of dimensions, the framework presented here can be directly ap-

plied. If multiple pairs are included in the same equation, the framework can be applied to coefficients from terms corresponding to each pair. In this case, the surface represented by each pair of dimensions represents the joint effects of those dimensions on the dependent variable, holding the effects of all other dimensions constant.

Although the framework presented here should prove useful in future studies of congruence, it nonetheless has several shortcomings. First, some aspects of the framework, particularly the jackknife procedure, are computationally intensive. In most cases, this should not pose major difficulties, given the widespread availability of high-speed computers. Second, the framework relies on numerous tests of significance, which may inflate Type I error rates. This may be controlled using the Bonferroni correction (Harris, 1985) or more powerful alternatives, such as the sequential procedures described by Holm (1979) and Holland and Copenhaver (1988).

Third, the jackknife procedure tends to overestimate known standard errors (Efron & Gong, 1983). This problem is accentuated by the presence of outliers, which may dramatically influence coefficient estimates and hence increase the variability of the coefficient estimates yielded by the jackknife procedure. This problem can be minimized by screening data for influential cases prior to analysis and either eliminating them or, if a large number is detected, modeling them separately using an indicator variable (Belsley, Kuh, & Welsch, 1980).

Fourth, like any application of regression analysis, this framework is based on the assumption that the component variables are measured without error (Pedhazur, 1982). This assumption can be relaxed when structural equations modeling is used (Bollen, 1989; Jöreskog & Sörbom, 1988). The resulting structural coefficients can be interpreted using the framework presented here, with the caveat that the x -, y -, and z -axes represent latent constructs rather than manifest variables. However, procedures for estimating structural coefficients on curvilinear and interactive terms are rather complex and have yet to attain widespread use (Bollen, 1989; Hayduk, 1987; Kenny & Judd, 1984). Furthermore, the jackknife procedure would require recalculating the sample covariance matrix N times, adding significant computational requirements when large samples are used. At this stage, perhaps the most advisable procedure is to ensure that component measures are highly reliable prior to analysis, thereby minimizing problems resulting from measurement error at subsequent stages (Edwards, in press).

A final issue is the interpretation of regression coefficients on lower-order terms, such as b_1 and b_2 in Equation 6, in the presence of higher-order terms. These coefficients are scale-dependent, meaning that adding or subtracting a constant to X or Y will change the estimated values and significance levels of b_1 and b_2 (Arnold & Evans, 1979; Cohen, 1978). Although this dependence may seem to render the interpretation of b_1 and b_2 meaningless, it simply reflects the fact that these coefficients represent conditional relationships, indicating the slope of the surface where both X and Y equal 0 (Aiken & West, 1991; Jaccard et al., 1990). Rescaling X and Y simply shifts the origin of the x - and y -axes, so that b_1 and b_2 describe the slope at a

different point on the surface. If rescaling moves the origin beyond the range of X and Y , then b_1 and b_2 are obviously not meaningful, because they represent estimates extrapolated beyond the bounds of the data. However, rescaling within the range of X and Y produces values of b_1 and b_2 that may yield useful interpretations. For example, if X and Y are centered at their means, b_1 and b_2 represent the slope of the surface at the mean of both X and Y (Cronbach, 1987). X and Y can be centered at other useful values, such as one standard deviation above or below their means (cf. Cohen & Cohen, 1983: 325). In our analyses, we centered X and Y at their scale midpoints, because these values are not sample-dependent and yield useful interpretations of b_1 and b_2 (the slope of the surface at the center of the plane bounded by the X and Y measures). It should be emphasized that these rescalings do not affect the correspondence between the surface and the data, because the calculated locations of the stationary point and principal axes change accordingly with the rescaling of X and Y . For more detailed discussions of the interpretation of coefficients on lower-order terms in polynomial regression equations, see Aiken and West (1991) and Jaccard and colleagues (1990).

CONCLUSION

The study of congruence in organizational research is currently at a critical juncture. For decades, research in this area has relied on difference scores, which introduce numerous substantive and methodological problems. These problems are sufficiently serious to render much of this research inconclusive. For example, a recent review of person–job fit studies conducted from 1960 through 1989 (Edwards, 1991) revealed that, due to the widespread use of difference scores, the results of these studies are largely inconclusive. This situation is not unique to the person–job fit literature but is evident in virtually every area of organizational research that uses difference scores to examine congruence (Edwards, in press; Mowday, 1987; Wanous et al., 1992; Van de Ven & Drazin, 1985). Fortunately, procedures such as the polynomial regression approach and the framework presented here are now available that avoid many problems with difference scores and more fully address questions of conceptual relevance in congruence research. If these procedures gain widespread acceptance, problems attributable to the use of difference scores in congruence research may be overcome, and significant theoretical and empirical advances are likely to occur.

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APPENDIX

The jackknife is a general nonparametric procedure for calculating the standard error of an expression (Efron & Gong, 1983; Peddada, 1992). The jackknife involves dropping one observation from a sample, calculating the expression of interest, and then replacing the excluded observation. This procedure is repeated until each observation has been dropped exactly once, so that the expression has been calculated n times using samples of the size $n - 1$. The resulting values are used to compute n "pseudovalues" of the expression of interest, using the following formula:

$$pv_i = nf(b) - (n - 1)f(b_{-i}), \quad (A1)$$

where

- pv_i = the i th pseudovalue,
- $f(b)$ = the expression of interest calculated using the coefficient estimates obtained from the entire sample,
- $f(b_{-i})$ = the expression calculated using the coefficient estimates obtained from the entire sample excluding the i th observation, and
- n = the sample size.

The jackknife estimate of the sample variance of the expression of interest is calculated as follows (Peddada, 1992):

$$s^2 = \frac{\sum_{i=1}^n (pv_i - \bar{pv})^2}{n(n - 1)}, \quad (A2)$$

where

$$\bar{pv} = \text{the mean of the } n \text{ pseudovalues.}$$

The ratio of the expression of interest to the square root of s^2 can be referred to ordinary t -tables, with $n - 1$ degrees of freedom.

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