Latent Variable Modeling in Congruence Research: Current Problems and Future Directions

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Latent Variable Modeling in Congruence Research

Current Problems and Future Directions

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During the past decade, the use of polynomial regression has become increasingly prevalent in congruence research. One drawback of polynomial regression is that it relies on the assumption that variables are measured without error. This assumption is relaxed by structural equation modeling with latent variables. One application of structural equation modeling to congruence research is the latent congruence model (LCM). Although the LCM takes measurement error into account and allows tests of measurement equivalence, it is framed around the mean and algebraic difference of the components of congruence (e.g., the person and organization), which creates various interpretational problems. This article discusses problems with the LCM and shows how these problems are resolved by a linear structural equation model that uses the components of congruence as predictors and outcomes. Extensions of the linear model to quadratic equations used in polynomial regression analysis are discussed.

Keywords: *congruence; difference scores; polynomial regression; latent variables; structural equation modeling*

The concept of congruence maintains a central position in organizational research. Congruence refers to the fit, match, similarity, or agreement between two constructs, such as the personal and organizational values (Chatman, 1989), employee needs and organization rewards (Dawis, 1992), job demands and employee abilities (Edwards, 1996), and organizational strategy and the environment (Venkatraman, 1989). Congruence has been related to various causes and outcomes at the individual, group, and organizational levels (Donaldson, 2001; Edwards, 1991; Kristof-Brown, Zimmerman, & Johnson, 2005; Spokane, Meir, & Catalano, 2000).

The study of congruence has progressed through various methodological stages. Early studies relied on difference scores and profile similarity indices (Edwards, 1991; Kristof, 1996), which are prone to numerous methodological problems (Cronbach, 1958; Edwards, 1994; Johns, 1981). Many of these problems are avoided by polynomial regression (Edwards, 1994, 2002; Edwards & Parry, 1993), which has gained prominence during the past decade. For instance, a recent meta-analysis of person–environment fit research (Kristof-Brown et al., 2005) indicated that polynomial regression was used in about 20% of studies published since the method was introduced. One limitation of polynomial regression is that it rests on the assumption that variables are measured without error (Berry, 1993). This assumption is relaxed by structural equation modeling with latent

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variables (Bollen, 1989; Kline, 2004; Loehlin, 2004), and work that integrates polynomial regression with structural equation modeling is under way (Edwards & Kim, 2002).

One recent application of structural equation modeling to the study of congruence is the latent congruence model (LCM) developed by Cheung (2007). The LCM treats the components of congruence (e.g., the person and environment) as first-order factors with fixed loadings on second-order factors intended to represent the congruence (i.e., algebraic difference) and level (i.e., mean) of the components. The LCM takes measurement error into account by specifying the components of congruence as latent variables with multiple indicators. Cheung (2007) also has demonstrated how the indicators of the components can be tested for measurement equivalence, which is important for interpreting the comparison of the components in terms of congruence.

From a measurement perspective, the LCM is a step forward in congruence research, given that measurement error can bias coefficient estimates in polynomial regression and lead to erroneous conclusions. However, from a substantive perspective, the LCM is a step backward for two reasons. First, the LCM is restricted to linear relationships and, therefore, cannot address curvilinear relationships, which are central to congruence research. For instance, person–organization fit research is based on the premise that outcomes such as job satisfaction, organizational commitment, and performance decrease when the person and organization differ from one another in either direction (Chatman, 1989; Kristof, 1996). This premise implies a curvilinear (i.e., inverted-U) relationship between congruence and outcomes. More generally, any study that uses a squared difference, absolute difference, Euclidean distance, or profile correlation to operationalize congruence implicitly rests on the assumption that the relationship between congruence and other variables is curvilinear (Edwards, 1994). Because the LCM is strictly linear, it cannot test curvilinear relationships or detect whether relationships predicted to be linear are, in fact, curvilinear.

Second, the LCM shifts attention from the components of congruence to the difference and mean of the components. This shift reintroduces problems with difference scores that polynomial regression was designed to solve. For instance, using the difference between two components as a predictor conceals the relationship between each component and the outcome (Edwards, 1994). This problem also occurs when the mean of the components is used as a predictor (Lichtenberg, 1990), as in the LCM. Similar problems occur when the difference and mean of the components are used as outcomes (Edwards, 1995). By obscuring relationships involving the components of congruence, the LCM invites interpretations that are misleading or incorrect. For instance, the difference and mean of two components can relate to an outcome, suggesting support for congruence and level effects, when both relationships represent nothing more than a relationship between one component and the outcome. Furthermore, as shown later, results that satisfy the definitions of level and congruence are antagonistic such that, if evidence for level is found, evidence for congruence is necessarily ruled out and vice versa.

This article identifies problems with the LCM and explains how these problems are avoided by using the components of congruence as predictors and outcomes. This approach clarifies the relationships associated with the components and yields results that can be used to test hypotheses that level and congruence represent. Results from this approach can also be used to compute any information yielded by the LCM, which raises further questions concerning the value of the LCM to congruence research. Although the

LCM takes measurement error into account and can be used to evaluate measurement equivalence, these features also characterize linear structural equation models that use components as predictors and outcomes. The article concludes with future directions for structural equation modeling in congruence research, highlighting recent work on quadratic structural equation models (Edwards & Kim, 2002).

Defining Level and Congruence

The distinguishing feature of the LCM is its use of the algebraic difference and mean of the components of congruence as predictors and outcomes of other variables. This feature of the LCM involves the structural equations that relate the latent component variables to other latent variables, not the measurement equations that relate the latent component variables to their indicators. As such, this article focuses on the structural equations that underlie the LCM. These equations are expressed with simple notation that clearly distinguishes level and congruence from the component variables and helps to convey the problems that the LCM creates. Structural equations for the LCM using conventional LISREL notation are provided by Cheung (2007), and LISREL syntax for the alternative linear structural equation model advocated in this article is given in Appendix A.

The mapping of level and congruence onto the component variables can be expressed in equation form. Drawing from Equations 1 and 2 of Cheung (2007), the component variables can be expressed as functions of level and congruence as follows:

$$Y_1 = L - .5C \tag{1}$$
$$Y_2 = L + .5C, \tag{2}$$

where Y_1 and Y_2 are component variables, L is level, and C is congruence. Solving for L and C yields expressions that correspond to Equations 3 and 4 of Cheung (2007):

$$L = .5(Y_1 + Y_2) \tag{3}$$
$$C = Y_2 - Y_1. \tag{4}$$

Equations 3 and 4 show that L and C are the mean and algebraic difference, respectively, of Y_1 and Y_2.

Several points concerning the definitions of L and C in Equations 3 and 4 should be underscored. First, L and C are exact functions of Y_1 and Y_2, as indicated by the absence of residuals in Equations 3 and 4. Therefore, any results generated by L and C can also be obtained from Y_1 and Y_2, as demonstrated later in this article. Second, C is not defined as the match between Y_1 and Y_2, such that C is maximized when Y_1 and Y_2 are equal. Rather, C increases as Y_2 increases toward Y_1 and continues to increase as Y_2 exceeds Y_1. Thus, when Y_2 is less than Y_1, an increase in C means that the match between Y_1 and Y_2 is increasing, whereas when Y_2 is greater than Y_1, an increase in C means that the match between Y_1 and Y_2 is decreasing. Hence, an increase in C does not necessarily mean that two variables are closer to one another, which is how congruence is usually conceptualized in research on fit, similarity, and agreement (Edwards, 1994). Rather, higher scores on C could mean that Y_1 and Y_2 are becoming closer together or further apart, depending on the relative magnitudes of Y_1 and Y_2.

A third point is that, when L and C are used as predictors or outcomes, the definitions of L and C imply specific patterns of relationships for Y_1 and Y_2. For instance, because L assigns equal weights of .5 to Y_1 and Y_2, using L as a predictor implies that Y_1 and Y_2 have equal effects on the outcome (Lichtenberg, 1990). Analogously, because C is an algebraic difference, it assigns equal but opposite weights of –1 and +1, respectively, to Y_1 and Y_2. As such, using C as a predictor implies that Y_1 and Y_2 have equal but opposite effects on the outcome (Edwards, 1994). Similarly, using L as an outcome implies that the causes of L have equal effects on Y_1 and Y_2, and using C as an outcome implies that the causes of C have equal but opposite effects on Y_1 and Y_2. The relationships for Y_1 and Y_2 implied by L and C follow from the definitions of L and C, and researchers attempting to interpret results for L and C are likely to infer the patterns described above. For example, if results show that L influences an outcome, it stands to reason that a researcher will interpret this result not as an effect for either Y_1 or Y_2 alone but rather as an effect that involves both Y_1 and Y_2, presumably with equal weights in light of how L is defined in Equation 3. Unfortunately, the coefficient on L provides no information about whether the effects of Y_1 and Y_2 are equal. Similar ambiguities arise when L is used as an outcome and when C is used as a predictor or outcome. These ambiguities undermine the interpretation of results for L and C and constitute what is perhaps the most serious drawback of the LCM. The following discussion traces the sources of these ambiguities and shows how they are avoided by replacing L and C with Y_1 and Y_2, supplemented by analyses that address conceptual issues that might motivate the use of L and C.

Level and Congruence as Predictors

To demonstrate the problems that occur when L and C are used as predictors, consider the following equation:

$$Z = a_0 + a_1 L + a_2 C + e, \quad (5)$$

where L and C are defined according to Equations 3 and 4, Z is the outcome, e is a residual, and a_0, a_1, and a_2 are unstandardized coefficients. Throughout this article, coefficients for L and C are labeled a_i, and coefficients for Y_1 and Y_2 are labeled b_i. Although this notation departs from the usual LISREL convention, it clearly differentiates models involving L and C versus Y_1 and Y_2. Traditional LISREL notation is used in the syntax provided in Appendix A.

A basic question concerning Equation 5 is how to interpret a_1 and a_2. This question might be addressed by considering how L and C are defined in Equations 3 and 4. As noted earlier, because L assigns the same weight of .5 to Y_1 and Y_2, a_1 would seem to represent equal effects of Y_1 and Y_2. Likewise, because C assigns equal but opposite weights of −1 and +1 to Y_1 and Y_2, a_2 appears to capture equal but opposite effects for Y_1 and Y_2. These interpretations of a_1 and a_2 are reinforced by substituting Equations 3 and 4 into Equation 5 and expanding:

$$Z = a_0 + a_1(.5[Y_1 + Y_2]) + a_2(Y_2 - Y_1) + e$$
$$= a_0 + .5a_1Y_1 + .5a_1Y_2 + a_2Y_2 - a_2Y_1 + e. \quad (6)$$

In Equation 6, the terms $.5a_1Y_1$ and $.5a_1Y_2$ result from the expansion of L. Because Y_1 and Y_2 have the same coefficient, it appears that a_1 implies equal effects of Y_1 and Y_2 on Z. Similarly, the terms a_2Y_2 and $-a_2Y_1$ are produced by the expansion of C, and given that these terms assign coefficients on Y_1 and Y_2 that have the same magnitude and opposite signs, it follows that a_2 implies equal but opposite effects of Y_1 and Y_2 on Z.

Although these interpretations of a_1 and a_2 might seem plausible, they are incorrect. The correct interpretations of a_1 and a_2 are revealed by collecting like terms in Equation 6 to obtain:

$$Z = a_0 + (.5a_1 - a_2)Y_1 + (.5a_1 + a_2)Y_2 + e. \quad (7)$$

Equation 7 shows that a_1 and a_2 are elements of compound coefficients on Y_1 and Y_2. Neither a_1 nor a_2 alone captures the magnitude or sign of the effects of Y_1 or Y_2 and, hence, whether these effects are consistent with the expansions of L or C in Equation 6. For instance, if Y_1 and Y_2 have equal effects, as implied by L, then the compound coefficients on Y_1 and Y_2 in Equation 7 would be equal, such that $.5a_1 - a_2 = .5a_1 + a_2$. Subtracting $.5a_1$ from both sides of this equality and adding a_2 to both sides yields $2a_2 = 0$, which simplifies to $a_2 = 0$. Hence, the extent to which Y_1 and Y_2 have equal effects on Z is not indicated by a_1, the coefficient on L, but rather by a_2, the coefficient on C. If a_2 equals 0, then the coefficients on Y_1 and Y_2 are equal. If a_2 differs from 0, the coefficients on Y_1 and Y_2 differ from one another by the value $2a_2$.[1]

Like a_1, a_2 does not itself indicate whether Y_1 and Y_2 have equal but opposite effects on Z, as implied by C. Rather, this condition holds when the compound coefficients on Y_1 and Y_2 in Equation 7 are equal in magnitude and opposite in sign, such that $.5a_1 - a_2 = -(.5a_1 + a_2)$, or $.5a_1 - a_2 = -.5a_1 - a_2$. Adding a_2 to both sides of this equality and solving for a_1 yields $a_1 = 0$. Thus, whether Y_1 and Y_2 have equal but opposite effects is indicated not by a_2, the coefficient on C, but rather by a_1, the coefficient on L. If $a_1 = 0$, then the compound coefficients on Y_1 and Y_2 reduce to $-a_2$ and a_2, respectively, such that Y_1 and Y_2 have equal but opposite effects. If a_1 differs from 0, the effects of Y_1 and Y_2 are unequal in magnitude and can have the same or different signs.

The relative magnitudes of a_1 and a_2 also have important implications for interpreting results from Equation 5. For instance, if $a_1 = 2a_2$, then the compound coefficient on Y_1 equals 0, and the compound coefficient on Y_2 equals a_1 (or equivalently, $2a_2$). In this case, the coefficients on L and C in Equation 5 simply reflect an effect of Y_2 on Z. Likewise, if $a_1 = -2a_2$, then the compound coefficient on Y_2 equals 0, and the compound coefficient on Y_1 equals a_1 (or equivalently, $-2a_2$). In this case, the coefficients on L and C in Equation 5 are driven solely by the effect of Y_1 on Z. From a conceptual standpoint, it seems pointless to draw conclusions about level and congruence when results merely represent the effect of one component variable (cf. Cronbach, 1958)

Interpretational problems created when L and C are used as predictors are avoided by the following equation, which uses Y_1 and Y_2 as predictors:

$$Z = b_0 + b_1 Y_1 + b_2 Y_2 + e. \tag{8}$$

Equation 8 directly captures the joint effects of Y_1 and Y_2 on Z, thereby avoiding ambiguities associated with L and C. Equation 8 can also be used to test hypotheses that represent level and congruence effects. For instance, to assess whether Y_1 and Y_2 have equal effects, as implied by the expansion of L in Equation 6, the equality $b_1 = b_2$ can be tested. Likewise, to determine whether Y_1 and Y_2 have equal but opposite effects, as implied by the expansion of C in Equation 6, the expression $b_1 = -b_2$ can be tested. More generally, Equation 8 can be used to obtain any information yielded by L and C, given that L and C are completely determined by Y_1 and Y_2. For instance, the coefficients on L and C can be computed by substituting Equations 1 and 2 into Equation 8 and rearranging terms, which produces:

$$\begin{aligned} Z &= b_0 + b_1(L - .5C) + b_2(L + .5C) + e \\ &= b_0 + (b_1 + b_2)L + .5(b_2 - b_1)C + e. \end{aligned} \tag{9}$$

Expressing the coefficients on L and C in this manner reveals the relative contributions of Y_1 and Y_2, as reflected by b_1 and b_2, thereby avoiding the ambiguities associated with a_1 and a_2. For instance, the compound coefficient $(b_1 + b_2)$ that precedes L would indicate whether an effect attributed to L was primarily or solely driven by either Y_1 or Y_2, based on the magnitudes of b_1 and b_2. Similar information is yielded by the compound coefficient $.5(b_2 - b_1)$ that precedes C.

To illustrate the problems created by using L and C as predictors, data were generated in which Y_1 and Y_2 had various relationships with Z, and structural equation models were estimated that used Y_1 and Y_2 or L and C as predictors, using LISREL 8.54 (Jöreskog & Sörbom, 2003). For simplicity, Y_1, Y_2, and Z were specified as single indicators of their corresponding latent variables with loadings fixed at unity and measurement error variances fixed at zero. Using single indicators simplifies the measurement model but has no effect on the specification of the structural equation model, which would be the same regardless of whether single or multiple indicators are used. L and C were specified as latent variables with paths to Y_1 and Y_2 fixed according to Equations 1 and 2 (Cheung, 2007). Scores for Y_1 and Y_2 were randomly drawn from a bivariate normal distribution in which Y_1 and Y_2 had zero means, unit variances, and a correlation of .30. Nine population structural equations were specified in which b_1 varied in .20 increments from .00 to .80 and then back to .00 and, concurrently, b_2 increased in .20 increments from −.80 to .80.[2] For each equation, residuals were randomly drawn from a standard normal distribution and weighted such that the R^2 for each equation was approximately .30. A sample size of 250 was used for all analyses, similar to that in the empirical example used by Cheung (2007). All data were generated using the BASIC model of SYSTAT 10 (Wilkinson, 2000).

Results from structural equations using L and C versus Y_1 and Y_2 as predictors are reported in Table 1. Consider the results for L. For the first five cases, the coefficients on L were positive and similar in size, suggesting uniformly strong support for a level effect. However, as noted earlier, level implies that the coefficients on Y_1 and Y_2 are equal, which cannot be determined from the coefficient on L. This condition can be assessed using Y_1 and Y_2 as predictors and determining whether $b_1 = b_2$, as indicated by imposing

Table 1
Results For Level and Congruence Versus Component Variables as Predictors

	L and C as Predictors		Y_1 and Y_2 as Predictors	
	L	C	Y_1	Y_2
Case 1	0.89**	0.46**	−0.02	0.91**
Case 2	0.92**	0.23**	0.23*	0.69**
Case 3	0.73**	0.04	0.33**	0.40**
Case 4	0.72**	−0.15*	0.52**	0.21**
Case 5	0.74**	−0.40**	0.77**	−0.03
Case 6	0.46**	−0.45**	0.68**	−0.23**
Case 7	0.02	−0.43**	0.44**	−0.41**
Case 8	−0.33**	−0.41**	0.24**	−0.58**
Case 9	−0.83**	−0.36**	−0.05	−0.78**

Note: $N = 250$. Table entries are unstandardized coefficients. Coefficients in columns labeled L and C are estimates of a_1 and a_2, respectively. Coefficients in columns labeled Y_1 and Y_2 are estimates of b_1 and b_2, respectively. For each case, estimates of a_1 and a_2 relate to estimates of b_1 and b_2 according to Equations 7 and 9 (within rounding error).
*$p < .05$. **$p < .01$.

this constraint on the model and testing the reduction in fit using the chi-square difference test. Results showed that the difference between b_1 and b_2 was significant for all but Case 3, $\Delta\chi^2(1) = 0.38$, $p > .05$. For Cases 1, 2, 4, and 5, the effect for L was driven primarily or solely by either Y_1 or Y_2.

Turning to C, coefficients for the last five cases indicate negative effects of similar magnitude for congruence. However, the coefficients on C conceal whether the coefficients on Y_1 and Y_2 were equal in magnitude and opposite in sign. Again, this condition can be assessed using Y_1 and Y_2 as predictors and testing the equality $b_1 = -b_2$. Imposing this constraint on the model significantly reduced fit for all but Case 7, $\Delta\chi^2(1) = 0.05$, $p > .05$). For Cases 5, 6, 8, and 9, the coefficient on C primarily or solely reflected the influence of either Y_1 or Y_2.

Combining the results for L and C reveals a consistent pattern. For L, the condition that Y_1 and Y_2 have equal coefficients is satisfied only when the coefficient on C is not significant. This property holds because testing $b_1 = b_2$ is equivalent to testing $b_1 - b_2 = 0$, which in turn implies $a_2 = 0$ given that $b_1 - b_2 = -2a_2$. This equality follows from Equations 7 and 8, which show that $b_1 = .5a_1 - a_2$ and $b_2 = .5a_1 + a_2$. Hence, $b_1 - b_2 = .5a_1 - a_2 - (.5a_1 + a_2) = -2a_2$. Likewise, for C, the condition that the coefficients on Y_1 and Y_2 are equal in magnitude but opposite in sign is satisfied only when the coefficient on L is not significant. This pattern results from the fact that testing $b_1 = -b_2$ is equivalent to testing $b_1 + b_2 = 0$, which implies $a_1 = 0$ given that $b_1 + b_2 = a_1$, as again indicated by the coefficients on Y_1 and Y_2 in Equations 7 and 8. Hence, support for level requires lack of support for congruence and vice versa, meaning that level and congruence effects cannot coexist.

It might be tempting to dismiss the conditions for level and congruence that follow from Equations 3 and 4, instead inferring support for level or congruence when either L or C has a significant coefficient. However, doing so would invite the conclusion that Cases 1, 5, and 9 in Table 1 indicate both level and congruence effects when, in each case, the outcome is related to only one component variable. Little is gained by invoking interpretations of level and congruence when only one component variable is related to the outcome. This problem is avoided when L and C are replaced by Y_1 and Y_2, which clarifies their relationship with the outcome and permits tests of the conditions implied by the definitions of level and congruence in Equations 3 and 4.

Level and Congruence as Outcomes

Problems that occur when L and C are used as predictors are similar to those that arise when L and C are treated as outcomes, as in the following equations:

$$L = a_{10} + a_{11}X + e_{\mathrm{L}} \tag{10}$$

$$C = a_{20} + a_{21}X + e_{\mathrm{C}}. \tag{11}$$

In Equations 10 and 11, L and C are defined as before, X is a predictor variable, and a_{10}, a_{11}, a_{20}, and a_{21} are unstandardized coefficients. Consider the interpretation of a_{11} and a_{21} in Equations 10 and 11. Given that L is defined as an equally weighted composite of Y_1 and Y_2, it is tempting to conclude that a_{11} represents equal effects of X on Y_1 and Y_2. Likewise, because C is defined as the algebraic difference between Y_1 and Y_2, it effectively assigns opposite weights to Y_1 and Y_2, and a_{21} would appear to capture equal but opposite effects of X on Y_1 and Y_2. These interpretations are seemingly reinforced by replacing L and C with expressions that describe their definitions, as given by Equations 3 and 4:

$$.5(Y_1 + Y_2) = a_{10} + a_{11}X + e_{\mathrm{L}} \tag{12}$$

$$Y_2 - Y_1 = a_{20} + a_{21}X + e_{\mathrm{C}}. \tag{13}$$

In Equation 12, a_{11} captures the relationship between X and the composite $.5(Y_1 + Y_2)$, which assigns equal weights of .5 to Y_1 and Y_2. Similarly, in Equation 13, a_{21} captures the relationship between X and the composite $Y_2 - Y_1$, which places equal but opposite weights of -1 and $+1$ on Y_1 and Y_2, respectively.

Although these interpretations of a_{11} and a_{21} might appear reasonable, they are incorrect. The correct interpretations are revealed by solving Equations 12 and 13 for Y_1 and Y_2. To solve for Y_1, Equation 13 is multiplied by .5, subtracted from Equation 12, and simplified to obtain:

$$Y_1 = a_{10} - .5a_{20} + (a_{11} - .5a_{21})X + e_{\mathrm{L}} - .5e_{\mathrm{C}}. \tag{14}$$

To solve for Y_2, Equation 13 is multiplied by .5, added to Equation 12, and simplified to yield:

$$Y_2 = a_{10} + .5a_{20} + (a_{11} + .5a_{21})X + e_{\mathrm{L}} + .5e_{\mathrm{C}}. \tag{15}$$

Equations 14 and 15 show that the effects of X on Y_1 and Y_2 are represented by the compound coefficients $(a_{11} - .5a_{21})$ and $(a_{11} + .5a_{21})$, respectively. Hence, neither a_{11} nor a_{21}

itself captures the effects of X on both Y_1 and Y_2, which in turn means that neither a_{11} nor a_{21} indicates whether these effects are consistent with the definitions of L and C in Equations 3 and 4. To illustrate, if the effects of X on Y_1 and Y_2 are equal, as implied by L, then $(a_{11} - .5a_{21}) = (a_{11} + .5a_{21})$, which simplifies to $a_{21} = 0$. Hence, whether the effects of X on Y_1 and Y_2 are equal is captured not by the coefficient on X when L is the outcome, but instead by the coefficient on X when C is the outcome. If $a_{21} = 0$, then the effects of X on Y_1 and Y_2 indicated by a_{11} are equal, whereas when a_{21} differs from 0, the effects of X on Y_1 and Y_2 differ by the value a_{21}. Conversely, if the effects of X on Y_1 and Y_2 are equal in magnitude but opposite in sign, as implied by C, then $(a_{11} - .5a_{21}) = -(a_{11} + .5a_{21})$, or $a_{11} - .5a_{21} = -a_{11} - .5a_{21}$. Adding a_{11} and $.5a_{21}$ to both sides of this expression yields $2a_{11} = 0$, which simplifies to $a_{11} = 0$. Thus, whether X has equal but opposite effects on Y_1 and Y_2 is represented by the coefficient on X not when C is the outcome, but when L is the outcome. If $a_{11} = 0$, the coefficients linking X to Y_1 and Y_2 are equal in magnitude and opposite in sign. If a_{11} differs from 0, the coefficients on X differ in magnitude and can have the same or different signs.

The interpretation of results from either Equations 10 or 11 also depends on the relative magnitudes of both a_{11} and a_{21}. For example, if $a_{21} = 2a_{11}$, then the compound coefficient linking X to Y_1 equals 0, and the compound coefficient linking X to Y_2 equals a_{21} (or equivalently, $2a_{11}$). In this case, coefficients from Equations 10 and 11 that appear to represent effects of X on both L and C simply reflect an effect of X on Y_2. Similarly, if $a_{21} = -2a_{11}$, the compound coefficient relating X to Y_2 equals 0, and the compound coefficient relating X to Y_1 equals a_{21} (or equivalently, $-2a_{11}$). In this case, coefficients from Equations 10 and 11 would suggest that X is related to both L and C when, in fact, X is simply related to Y_1. Little is gained by drawing inferences about level and congruence when X is merely related to one component variable.

The foregoing problems are avoided by using Y_1 and Y_2 as outcomes, as follows:

$$Y_1 = b_{10} + b_{11}X + e_1 \quad (16)$$

$$Y_2 = b_{20} + b_{21}X + e_2. \quad (17)$$

Together, Equations 16 and 17 give estimates of the joint relationships of X with both Y_1 and Y_2. Coefficients from these equations can also be used to test hypotheses stated in terms of level and congruence. For example, to determine whether X has equal effects on Y_1 and Y_2, as implied when L is used as an outcome, the equality $b_{11} = b_{21}$ can be tested. Similarly, to assess whether the effects of X on Y_1 and Y_2 are equal in magnitude but opposite in sign, as implied when C is used as an outcome, the equality $b_{11} = -b_{21}$ can be tested. Other questions that might motivate the use of Equations 10 and 11 can be answered using estimates from Equations 16 and 17, given that the coefficients from these equations can be used to compute the coefficients that would be obtained from estimating Equations 10 and 11. The required expressions are given by substituting Equations 1 and 2 into Equations 16 and 17, as follows:

$$L - .5C = b_{10} + b_{11}X + e_1 \quad (18)$$

$$L + .5C = b_{20} + b_{21}X + e_2. \quad (19)$$

Coefficients that would result from using L as an outcome are found by adding Equations 18 and 19 and multiplying both sides by .5, which yields:

$$L = .5(b_{10} + b_{20}) + .5(b_{11} + b_{21})X + .5(e_1 + e_2). \tag{20}$$

Comparing Equations 10 and 20 shows that $a_{10} = .5(b_{10} + b_{20})$ and $a_{11} = .5(b_{11} + b_{21})$. Similarly, coefficients that would result from using C as an outcome are given by subtracting Equation 18 from Equation 19 and collecting like terms, which produces:

$$C = b_{20} - b_{10} + (b_{21} - b_{11})X + e_2 - e_1. \tag{21}$$

Comparing Equations 11 and 21 indicates that $a_{20} = b_{20} - b_{10}$ and $a_{21} = b_{21} - b_{11}$. Expressing the coefficients linking X to L and C in this manner reveals the extent to which these coefficients are determined by the effects of X on Y_1 and Y_2. These expressions also show that a_{11} is the average of the effects of X on Y_1 and Y_2, and a_{21} is the difference between these effects. Although the average and difference of these effects might be relevant to certain research questions, focusing exclusively on these quantities is ill advised, because doing so is tantamount to using L and C as outcomes and disregarding the relationships of X with Y_1 and Y_2.

To demonstrate the problems that occur when L and C are used as outcomes, data were generated in which X had various relationships with Y_1 and Y_2, and structural equation models were estimated in which Y_1 and Y_2 or L and C were treated as outcomes. As before, X, Y_1, and Y_2 were specified as single indicators of their associated latent variables with loadings fixed at unity and measurement error variances fixed at zero, and paths relating L and C to Y_1 and Y_2 were fixed according to Equations 1 and 2. Scores for X were randomly drawn from a standard normal distribution, and nine population structural equations were specified for both Y_1 and Y_2. The coefficients relating X to Y_1 varied in .20 increments from .00 to .80 and back down to .00. Simultaneously, the coefficients relating X to Y_2 increased in .20 increments from –.80 to .80. Residuals for Y_1 and Y_2 were randomly drawn from a standard normal distribution and assigned weights to produce R^2 values of approximately .30 for each structural equation. As before, the sample size was set at 250, data were generated using SYSTAT 10, and models were estimated with LISREL 8.54.

Results from structural equation models using L and C versus Y_1 and Y_2 as outcomes are provided in Table 2. For the first five cases, the coefficients relating X to L were positive and comparable in size, suggesting a level effect. However, as shown earlier, the coefficient relating X to L does not itself indicate whether X has equal effects on Y_1 and Y_2, such that $b_{11} = b_{21}$. This equality can be assessed by specifying Y_1 and Y_2 as outcomes and testing the reduction in fit produced by the constraint $b_{11} = b_{21}$. Results indicated that the difference between b_{11} and b_{21} was significant for all but Case 3, $\Delta\chi^2(1) = 0.09$, $p > .05$. For Cases 1, 2, 4, and 5, the coefficients on Y_1 and Y_2 were significantly different, such that the coefficient linking X to L was driven primarily or solely by the relationship between X and either Y_1 or Y_2. Thus, the coefficients on L concealed substantial variability in the coefficients relating X to Y_1 and Y_2, and for Cases 1 and 5, an apparent relationship between X and L was actually a bivariate relationship between X and either Y_1 or Y_2.

Table 2
Results for Level and Congruence Versus Component Variables as Outcomes

	L and C as Outcomes		Y_1 and Y_2 as Outcomes	
Case 1	L	0.40**	Y_1	0.04
	C	0.72**	Y_2	0.76**
Case 2	L	0.46**	Y_1	0.26**
	C	0.40**	Y_2	0.66**
Case 3	L	0.42**	Y_1	0.41**
	C	0.02	Y_2	0.43**
Case 4	L	0.38**	Y_1	0.59**
	C	−0.43**	Y_2	0.16**
Case 5	L	0.45**	Y_1	0.87**
	C	−0.84**	Y_2	0.03
Case 6	L	0.17**	Y_1	0.62**
	C	−0.90**	Y_2	−0.28**
Case 7	L	−0.03	Y_1	0.38**
	C	−0.83**	Y_2	−0.45**
Case 8	L	−0.20**	Y_1	0.22**
	C	−0.83**	Y_2	−0.61**
Case 9	L	−0.48**	Y_1	−0.06
	C	−0.85**	Y_2	−0.91**

Note: $N = 250$. Table entries are unstandardized regression coefficients relating X to either L and C or Y_1 and Y_2 as outcomes. Coefficients to the right of L and C are estimates of a_{11} and a_{21}, respectively. Coefficients to the right of Y_1 and Y_2 are estimates of b_{11} and b_{21}, respectively. For each case, estimates of a_{11} and a_{21} relate to estimates of b_{11} and b_{21} according to Equations 14, 15, 20, and 21 (within rounding error).
$^{*}p < .05$. $^{**}p < .01$.

When C is used as the outcome, results for the last five cases produced coefficients on X of similar magnitude, each suggesting a negative relationship with congruence. However, these coefficients do not reveal whether X has equal but opposite relationships with Y_1 and Y_2. When Y_1 and Y_2 were used as outcomes, the coefficients on X were consistent with the equality $b_{11} = -b_{21}$ only for Case 7, where imposing this constraint did not significantly reduce the fit of the model, $\Delta\chi^2(1) = 0.84$, $p < .05$. For Cases 5, 6, 8, and 9, the coefficient linking X and C was driven primarily by the relationship between X and either Y_1 or Y_2.

Taken together, the results for L and C as outcomes follow a pattern similar to that when L and C are used as predictors. In particular, the condition implied by L in which X has equal effects on Y_1 and Y_2 is satisfied only when the coefficient linking X to C is not significant. This result is due to the fact that testing $b_{11} = b_{21}$ is equivalent to testing $b_{11} - b_{21} = 0$, which in turn is equivalent to testing $a_{21} = 0$ given that $a_{21} = b_{21} - b_{11}$. Conversely, the condition associated with C in which X has equal but opposite effects on Y_1 and Y_2 is fulfilled only when the coefficient relating X to L is not significant. This outcome occurs because testing $b_{11} = -b_{21}$ is the same as testing $b_{11} + b_{21} = 0$, which, in turn, is the same as testing $a_{11} = 0$ given that $a_{11} = .5(b_{11} + b_{21})$. Thus, evidence for level requires the lack of evidence for congruence and vice versa, meaning that a predictor cannot have effects on both level and congruence.

Again, it might be argued that effects on level and congruence should be inferred solely from a_{11} and a_{21}, respectively, without requiring equal effects for level and opposite effects for congruence. However, this approach would treat Cases 1, 5, and 9 in Table 2 as examples of both level and congruence, even though X is related to only Y_1 or Y_2. Bivariate relationships such as these hardly justify complex interpretation in terms of level and congruence. By using Y_1 and Y_2 instead of L and C as outcomes, the relationships of X with Y_1 and Y_2 are clarified, and conditions implied by using L and C as outcomes can be directly tested.

Level and Congruence as Predictors and Outcomes

When L and C are used as both predictors and outcomes, their interpretational problems are compounded. To distinguish between L and C as predictors versus outcomes, the notation used up to this point is modified. L and C as predictors are expressed as follows:

$$\mathrm{L_X} = .5(X_1 + X_2) \tag{22}$$

$$C_\mathrm{X} = X_2 - X_1. \tag{23}$$

The subscript X designates L and C as predictors, and the component predictor variables are X_1 and X_2. L and C as outcomes are written as follows:

$$L_\mathrm{Y} = .5(Y_1 + Y_2) \tag{24}$$

$$C_\mathrm{Y} = Y_2 - Y_1. \tag{25}$$

Here, the subscript Y indicates that L and C are outcomes. As before, the component outcome variables are Y_1 and Y_2. Equations that combine L_X, C_X, L_Y, and C_Y as predictors and outcomes can be written as follows:

$$L_\mathrm{Y} = a_{10} + a_{11}L_\mathrm{X} + a_{12}C_\mathrm{X} + e_\mathrm{L} \tag{26}$$

$$C_\mathrm{Y} = a_{20} + a_{21}L_\mathrm{X} + a_{22}C_\mathrm{X} + e_\mathrm{C}. \tag{27}$$

We now consider the interpretation of the coefficients in Equation 26 and 27. Based on the definitions of L_X in Equation 22, it would seem that the coefficients on L_X represent equal effects of X_1 and X_2 on both L_Y and C_Y. Likewise, given the definition of C_X in Equation 23, the coefficients on C_X imply equal but opposite effects of X_1 and X_2 on L_Y and C_Y. However, these interpretations are again incorrect, as seen by substituting Equations 22 and 23 into Equations 26 and 27 and simplifying to obtain:

$$L_\mathrm{Y} = a_{10} + (.5a_{11} - a_{12})X_1 + (.5a_{11} + a_{12})X_2 + e_\mathrm{L} \tag{28}$$

$$C_\mathrm{Y} = a_{20} + (.5a_{21} - a_{22})X_1 + (.5a_{21} + a_{22})X_2 + e_\mathrm{C}. \tag{29}$$

Like Equation 7, Equations 28 and 29 show that the coefficients on L_X and C_X are elements of compound coefficients on X_1 and X_2. If X_1 and X_2 have equal effects on L_Y

and C_Y, as implied by using L_X as a predictor, then the coefficients on C_X (i.e., a_{12} and a_{22}) must be zero. Under this condition, the coefficients on X_1 and X_2 reduce to $.5a_{11}$ in Equation 28 and $.5a_{21}$ in Equation 29. Conversely, if X_1 and X_2 have equal but opposite effects on L_Y and C_Y, as implied when C_X is used as a predictor, then the coefficients on L_X (i.e., a_{11} and a_{21}) must be zero. In this case, the coefficients on X_1 and X_2 are $-a_{12}$ and a_{12} in Equation 28 and $-a_{22}$ and a_{22} in Equation 29.

Although Equations 28 and 29 resolve ambiguities created when L_X and C_X are used as predictors, the interpretation of these equations remains problematic due to the use of L_Y and C_Y as outcomes. These problems are addressed by substituting Equations 24 and 25 into Equations 28 and 29 and solving for Y_1 and Y_2, which yields:

$$Y_1 = a_{10} - .5a_{20} + (.5a_{11} - a_{12} - .25a_{21} + .5a_{22})X_1 + (.5a_{11} + a_{12} - .25a_{21} - .5a_{22})X_2 + e_L - .5e_C \quad (30)$$

$$Y_2 = a_{10} + .5a_{20} + (.5a_{11} - a_{12} + .25a_{21} - .5a_{22})X_1 + (.5a_{11} + a_{12} + .25a_{21} + .5a_{22})X_2 + e_L + .5e_C. \quad (31)$$

Equations 30 and 31 express the coefficients from Equations 26 and 27 as elements of compound coefficients linking X_1 and X_2 to Y_1 and Y_2. These expressions can be used to identify patterns of coefficients from Equations 26 and 27 implied by using L_X and C_X as predictors and L_Y and C_Y as outcomes. For instance, using L_X implies that the compound coefficients in Equation 30 are equal, or $.5a_{11} - a_{12} - .25a_{21} + .5a_{22} = .5a_{11} + a_{12} - .25a_{21} -.5a_{22}$. This equality simplifies to $2a_{12} = a_{22}$. Using L_X also implies that the compound coefficients in Equation 31 are equal, such that $.5a_{11} - a_{12} + .25a_{21} - .5a_{22} = .5a_{11} + a_{12} + .25a_{21} + .5a_{22}$, which reduces to $2a_{12} = -a_{22}$. Hence, using L_X as a predictor implies that the equalities $2a_{12} = a_{22}$ and $2a_{12} = -a_{22}$ both hold. Treating these equalities as simultaneous equations and solving for a_{12} and a_{22} yields $a_{12} = 0$ and $a_{22} = 0$, meaning that the coefficients on C_X in Equations 26 and 27 are both zero. Analogously, using C_X implies that the compound coefficients on X_1 and X_2 are equal in magnitude but opposite in sign. For Equation 30, this condition can be written as $.5a_{11} - a_{12} - .25a_{21} + .5a_{22} = -.5a_{11} -a_{12} + .25a_{21} + .5a_{22}$, which reduces to $a_{11} = .5a_{21}$. For Equation 31, the condition means that $.5a_{11} - a_{12} + .25a_{21} - .5a_{22} = -.5a_{11} - a_{12} - .25a_{21} - .5a_{22}$, or $a_{11} = -.5a_{21}$. Combining these equalities and solving for a_{11} and a_{21} gives $a_{11} = 0$ and $a_{21} = 0$, such that the coefficients on L_X in Equations 26 and 27 are both zero.

Turning to L_Y and C_Y as outcomes, using L_Y implies that the coefficients on X_1 are equal across Equations 30 and 31. This equality can be written as $.5a_{11} - a_{12} - .25a_{21} + .5a_{22} = .5a_{11} - a_{12} + .25a_{21} - .5a_{22}$, which simplifies to $.5a_{21} = a_{22}$. Using L_Y also implies that the coefficients on X_2 are equal, such that $.5a_{11} + a_{12} - .25a_{21} - .5a_{22} = .5a_{11} + a_{12} + .25a_{21} + .5a_{22}$, or $.5a_{21} = -a_{22}$. When combined, the equalities $.5a_{21} = a_{22}$ and $.5a_{21} = -a_{22}$ are satisfied when $a_{21} = 0$ and $a_{22} = 0$. Hence, using L_Y as an outcome implies that the coefficients on L_X and C_X in the equation using C_Y as the outcome are both zero. Conversely, using C_Y implies that the coefficients on X_1 in Equations 30 and 31 are equal in magnitude but opposite in sign, such that $.5a_{11} - a_{12} - .25a_{21} + .5a_{22} = -.5a_{11} + a_{12} - .25a_{21} + .5a_{22}$, or $a_{11} = 2a_{12}$. Using C_Y also implies that the coefficients on X_2 are equal in magnitude but opposite in sign, which translates into $.5a_{11} + a_{12} - .25a_{21} - .5a_{22} =$

$-.5a_{11} - a_{12} - .25a_{21} - .5a_{22}$, or $a_{11} = -2a_{12}$. In conjunction, the equalities $a_{11} = 2a_{12}$ and $a_{11} = -2a_{12}$ indicate that $a_{11} = 0$ and $a_{12} = 0$. Thus, using C_Y as an outcome means that the coefficients on L_X and C_X in the equation using L_Y as the outcome are both zero.

Integrating these conditions reveals patterns of coefficients implied when L_X and C_X are combined with L_Y and C_Y. For example, combining the conditions for L_X and L_Y yields $a_{12} = 0$, $a_{21} = 0$, and $a_{22} = 0$, such that the only nonzero coefficient is a_{11}, the coefficient on L_X predicting L_Y. Similarly, combining the conditions for C_X and L_Y gives $a_{11} = 0$, $a_{21} = 0$, and $a_{22} = 0$, meaning the only nonzero coefficient is a_{12}, the coefficient on C_X predicting L_Y. The conditions for L_X and C_Y combine into $a_{11} = 0$, $a_{12} = 0$, and $a_{22} = 0$, such that the only nonzero coefficient is a_{21}, which relates L_X to C_Y. Finally, the conditions for C_X and C_Y combine into $a_{11} = 0$, $a_{12} = 0$, and $a_{21} = 0$, leaving the only nonzero coefficient a_{22}, which links C_X to C_Y. In each case, the coefficient linking the predictor to the outcome is insensitive to whether the conditions implied by the predictor and outcome are fulfilled. Rather, these conditions are reflected by the other three coefficients, which differ from zero when the conditions for the predictor and outcome are violated. Hence, evidence that supports any single relationship between a predictor and outcome necessarily rules out the other three relationships.

The ambiguities associated with L_X, C_X, L_Y, and C_Y are avoided when X_1 and X_2 are used as predictors of Y_1 and Y_2:

$$Y_1 = b_{10} + b_{11}X_1 + b_{12}X_2 + e_1 \quad (32)$$

$$Y_2 = b_{20} + b_{21}X_1 + b_{22}X_2 + e_2. \quad (33)$$

Coefficients from Equations 32 and 33 can be used to test hypotheses that might motivate the use of L_X, C_X, L_Y, and C_Y. For example, using L_X as a predictor implies that $b_{11} = b_{12}$ and $b_{21} = b_{22}$, and using L_Y as an outcome implies that $b_{11} = b_{21}$ and $b_{12} = b_{22}$. In combination, these conditions mean that all four coefficients on X_1 and X_2 are equal. Similarly, using C_X as a predictor implies that $b_{11} = -b_{12}$ and $b_{21} = -b_{22}$, and using C_Y as a predictor implies that $b_{11} = -b_{21}$ and $b_{12} = -b_{22}$. Combining these conditions yields $b_{11} = -b_{12} = -b_{21} = b_{22}$. Other equalities can be derived to test coefficient patterns implied by L_X as a predictor of C_Y and C_X as a predictor of L_Y. If desired, the coefficient in Equation 32 and 33 can also be used to compute the coefficients that would be produced by Equations 26 and 27. The required expressions are obtained by solving Equations 22, 23, 24, and 25 for X_1, X_2, Y_1, and Y_2, substituting the resulting equalities into Equations 32 and 33 and rearranging terms, which yields the following (for details, see Appendix B):

$$\begin{aligned} L_Y = {} & .5(b_{10} + b_{20}) + .5(b_{11} + b_{12} + b_{21} + b_{22})L_X \\ & + .25(b_{12} - b_{11} + b_{22} - b_{21})C_X + .5(e_1 + e_2) \end{aligned} \quad (34)$$

$$\begin{aligned} C_Y = {} & b_{20} - b_{10} + (b_{21} - b_{11} + b_{22} - b_{12})L_X \\ & + .5(b_{11} - b_{12} - b_{21} + b_{22})C_X + e_2 - e_1. \end{aligned} \quad (35)$$

Equations 34 and 35 show that any information obtained from L_X, C_X, L_Y, and C_Y can be derived from X_1, X_2, Y_1, and Y_2. However, the value of computing the coefficients on L_X, C_X, L_Y, and C_Y is questionable in light of the ambiguities they create.

Table 3
Results for Level and Congruence Versus Component Variables as Predictors and Outcomes

		L_X and C_X as Predictors and L_Y and C_Y as Outcomes			X_1 and X_2 as Predictors and Y_1 and Y_2 as Outcomes	
		L_X	C_X		X_1	X_2
Case 1	L_Y	1.12**	0.22**	Y_1	0.84**	0.80**
	C_Y	−1.04**	0.48**	Y_2	−0.16	0.76**
Case 2	L_Y	0.86**	0.03	Y_1	0.40**	0.51**
	C_Y	−0.10	−0.06	Y_2	0.41**	0.40**
Case 3	L_Y	0.43**	−0.22**	Y_1	0.01	0.08
	C_Y	0.67**	−0.52**	Y_2	0.86**	−0.10
Case 4	L_Y	0.01	−0.43**	Y_1	0.48**	−0.47**
	C_Y	0.01	0.09	Y_2	0.40**	−0.38**
Case 5	L_Y	−0.06	−0.39**	Y_1	0.77**	0.01
	C_Y	−1.69**	−0.01	Y_2	−0.07	−0.84**
Case 6	L_Y	−0.01	−0.05	Y_1	0.40**	0.41**
	C_Y	−1.64**	−0.11	Y_2	−0.31**	−0.52**
Case 7	L_Y	−0.37**	0.11*	Y_1	0.08	−0.03
	C_Y	−0.85**	0.34**	Y_2	−0.68**	−0.11
Case 8	L_Y	−0.03	0.04	Y_1	0.36**	−0.44**
	C_Y	0.10	0.88**	Y_2	−0.47**	0.49**
Case 9	L_Y	0.39**	−0.19**	Y_1	0.78**	−0.73**
	C_Y	0.69**	1.13**	Y_2	−0.01	0.74**

Note: $N = 250$. Table entries are unstandardized coefficients. In the columns labeled L_X and C_X, the coefficients to the right of L_Y are a_{11} and a_{12}, and the coefficients to the right of C_Y are a_{21} and a_{22}, respectively. In the columns labeled X_1 and X_2, the coefficients to the right of Y_1 are b_{11} and b_{12}, and the coefficients to the right of Y_2 are b_{21} and b_{22}, respectively. For each case, estimates of a_{11}, a_{12}, a_{21}, and a_{22} relate to estimates of b_{11}, b_{12}, b_{21}, and b_{22} according to Equations 30, 31, 34, and 35 (within rounding error).
*$p < .05$. **$p < .01$.

Problems that result from using L_X and C_X as predictors and L_Y and C_Y as outcomes are illustrated using artificial data in which X_1 and X_2 had various relationships with Y_1 and Y_2. Again, X_1, X_2, Y_1, and Y_2 were specified as single indicators of their respective latent variables with loadings fixed to unity and measurement error variances fixed to zero. Paths relating L_X, C_X, L_Y, and C_Y to X_1, X_2, Y_1, and Y_2 were fixed according to Equations 22 through 25. X_1 and X_2 were drawn from a bivariate normal distribution with zero means, unit variances, and a correlation of .30. Nine population equations were generated for both Y_1 and Y_2 in which b_{11}, b_{12}, b_{21}, and b_{22} had values ranging from −.80 to .80 in .40 increments. Combinations of these coefficients were chosen to include cases in which the conditions for level or congruence as a predictor or outcome were satisfied as well as cases in which support for level or congruence is partial or absent. Residuals were randomly drawn from a standard normal distribution and weighted to produce R^2 values averaging .30 for both Y_1 and Y_2. For each equation, a sample size of 250 was again used. Data were generated with SYSTAT 10, and models were estimated using LISREL 8.54. Results are reported in Table 3, and as before, selected aspects of these results are discussed to demonstrate the issues at hand.

First, consider the relationship between L_X and L_Y. For Cases 1, 2, and 3, the coefficients linking L_X to L_Y is positive and significant. However, as noted earlier, these coefficients do not reveal whether X_1 and X_2 have equal effects on both Y_1 and Y_2, as implied by L_X and L_Y. This pattern was evident only for Case 2, for which the coefficients relating X_1 and X_2 to Y_1 and Y_2 were similar in magnitude. Constraining these coefficients to be equal did not significantly reduce the fit of the model, $\Delta\chi^2(3) = 1.32$, $p > .05$, indicating that the conditions implied by using L_X to predict L_Y were tenable. In contrast, imposing these constraints reduced model fit for Case 1, $\Delta\chi^2(3) = 90.22$, $p < .05$, and Case 3, $\Delta\chi^2(3) = 68.40$, $p < .057$. Moreover, for Case 1, X_1 was not significantly related to Y_2, whereas for Case 3, the only significant relationship was between X_1 and Y_2. The differences among these results would go undetected by focusing on the relationship between L_X and L_Y.

We now turn to the relationship between C_X and L_Y. For Cases 3, 4, and 5, the coefficient relating C_X to L_Y was negative and significant. Again, these coefficients are insensitive to the conditions implied by C_X and L_Y, whereby X_1 and X_2 have equal but opposite effects on both Y_1 and Y_2, and the magnitudes of these effects are equal across Y_1 and Y_2. This pattern was consistent with Case 4, as shown by the results for X_1 and X_2 as predictors of Y_1 and Y_2. Imposing this pattern of constraints did not significantly reduce the fit of the model for Case 4, $\Delta\chi^2(3) = 0.91$, $p > .05$. However, these constraints were rejected for Case 3, $\Delta\chi^2(3) = 81.29$, $p < .05$, and Case 5, $\Delta\chi^2(3) = 116.60$, $p < .05$. Furthermore, the coefficients relating X_1 and X_2 to Y_1 and Y_2 were markedly different across Cases 3, 4, and 5, as seen by inspecting Table 3.

Concerning the relationship between L_X and C_Y, results for Cases 5, 6, and 7 each yielded significant negative coefficients. However, only Case 6 evidenced the pattern implied by L_X and C_Y in which the coefficients on X_1 and X_2 were equal within each equation for Y_1 and Y_2 but opposite in sign across the Y_1 and Y_2 equations. Constraining the coefficients to follow this pattern did not significantly reduce model fit for Case 6, $\Delta\chi^2(3) = 2.63$, $p > .05$, but worsened model fit for Case 5, $\Delta\chi^2(3) = 68.66$, $p < .05$, and Case 7, $\Delta\chi^2(3) = 39.92$, $p < .05$. Again, the pattern of coefficients relating X_1 and X_2 to Y_1 and Y_2 differed considerably across Cases 5, 6, and 7, differences that are obscured by the similar results for the coefficient relating L_X to C_Y.

Finally, the coefficient linking C_X to C_Y was positive and significant for Cases 7, 8, and 9. However, results for X_1 and X_2 as predictors of Y_1 and Y_2 revealed that only the coefficients for Case 8 were consistent with the pattern implied by C_X and C_Y, when X_1 and X_2 have equal but opposite relationships for both Y_1 and Y_2, and the relationships for X_1 and X_2 are equal but opposite across Y_1 and Y_2. For Case 8, imposing this pattern of coefficients on the model did not significantly reduce model fit, $\Delta\chi^2(3) = 1.34$, $p > .05$. However, this pattern of constraints was rejected for Case 7, $\Delta\chi^2(3) = 55.82$, $p < .05$, and Case 9, $\Delta\chi^2(3) = 69.96$, $p < .05$. Moreover, for Case 7, the only significant relationship was between X_1 and Y_2, whereas for Case 9, the only nonsignificant relationship was between X_1 and Y_2. These and other differences in the results for Cases 7, 8, and 9 are not evident from the coefficient relating C_X to C_Y.

Combining the results for L_X, C_X, L_Y, and C_Y highlights several key points. First, consistent with the derivations that follow Equations 30 and 31, evidence that supports any one relationship linking L_X and C_X to L_Y and C_Y simultaneously refutes the other three relationships. Therefore, only one of the four possible relationships can exist for a given data set.

Allowing for more than one relationship denies the definitions of L_X, C_X, L_Y, and C_Y in Equations 22 through 25 and invites conclusions that are more complex than justified by the data. For example, Cases 3 and 7 suggested that all four relationships between L_X, C_X, L_Y, and C_Y were supported when, in fact, the only significant relationship was between X_1 and Y_2. It hardly seems worthwhile to draw inferences about level and congruence predicting level and congruence based on a single bivariate relationship. Cases 1 and 9 also yielded four significant relationships between L_X, C_X, L_Y, and C_Y. However, for these cases, Y_1 was related to both X_1 and X_2, whereas Y_2 was only related to X_2. For Case 1, the coefficients relating X_1 and X_2 to Y_1 did not significantly differ, as implied by L_X, $\Delta\chi^2(3) = 0.06$, $p > .05$, whereas for Case 9, the coefficients linking X_1 and X_2 to Y_1 were opposite in sign and not significantly different in magnitude, as implied by C_X, $\Delta\chi^2(3) = 0.20$, $p > .05$. Hence, results for Cases 1 and 9 indicate a simple bivariate relationship between X_2 and Y_2, along with support for level and congruence, respectively, for X_1 and X_2 predicting Y_1. These patterns are obscured by results based on L_X, C_X, L_Y, and C_Y.

Reanalysis of Data From Cheung (2007)

The data used in the preceding examples demonstrate problems that occur when level and congruence are used as predictors, outcomes, or both. These problems can also be illustrated using data analyzed by Cheung (2007), as shown below. The Cheung (2007) data produce a limited pattern of relationships, which makes it less effective than the artificial data used earlier to illustrate the problems under consideration here. Nonetheless, the following reanalyses show that the problems demonstrated up to this point are not limited to the particular data generated for illustration.

The Cheung (2007) data contained responses from 220 managers and their supervisors on 24 items. These items were assigned to eight factors, with 3 items per factor. The eight factors represented perceptions of managers and supervisors on four aspects of the manager's behavior, including leadership, communication, planning and organizing, and customer service. The model examined by Cheung contained eight first-order factors representing manager and supervisor perceptions of leadership, communication, planning and organizing, and customer service, along with eight second-order factors representing level and congruence for the same four dimensions. The loadings of the first-order factors on the second-order factors were fixed according to Equations 1 and 2, such that the level and congruence factors represented the mean and difference, respectively, of their corresponding first-order factors. Cheung (2007) analyzed two versions of this model, one that treated level and congruence on leadership, communication, planning and organizing as predictors of level and congruence on customer service, and a second model that specified manager and supervisor perceptions of leadership, communication, planning and organizing as predictors of manager and supervisor perceptions of customer service.

The following reanalysis retained the eight first-order factors used by Cheung (2007) but dropped the eight second-order factors. The resulting model treated manager and supervisor perceptions of leadership, communication, and planning and organizing as correlated exogenous variables and manager and supervisor perceptions of customer service as endogenous variables with correlated residuals. All paths relating the six exogenous variables to the two endogenous variables were freely estimated. These paths were also used to compute paths that would result from analyzing level and congruence rather than manager and supervisor perceptions, based on Equations 34 and 35. These computations were conducted using the additional parameters function of LISREL, which also yields standard errors of the computed values. Hence, the model used to reanalyze the Cheung (2007) data yields the same information as that produced by the model examined by Cheung but is simpler, in that it does not require the specification of second-order level and congruence factors. LISREL syntax for the model analyzed here is given in Appendix A.

Results from the model used for reanalysis are reported in Table 4. The top panel contains coefficients directly estimated by the model, and the bottom panel gives coefficients computed by the additional parameters function. Several aspects of these results are worth noting. First, as expected, the results in Table 4 match those reported by Cheung (2007), confirming that results produced by the LCM can be obtained without second-order factors representing level and congruence. Second, as indicated by the top panel, only three coefficients relating manager and supervisor perceptions were significant, each of which involved a relationship between perceptions reported by the same person. Third, none of the coefficient patterns in the upper panel indicate support for level or congruence as predictors of level or congruence. The closest instance involved planning and organizing, for which the pattern of coefficients was consistent with level predicting level. In line with this pattern, the bottom panel shows that the only significant coefficient for planning and organizing involved level predicting level, as expected when the four coefficients in the upper panel do not differ from one another. However, the upper panel also indicates that the four coefficients for planning and organizing did not differ from zero, which invalidates the apparent evidence for level in the bottom panel. Finally, for communication, the bottom panel suggests support for level predicting level and congruence predicting congruence, even though both relationships cannot coexist. This apparent contradiction is resolved by the results in the upper panel, which show that the results for level and congruence represent nothing more than relationships between perceptions reported by the same person.

Tests of the patterns of coefficients for level and congruence predicting level and congruence are reported in Table 5. These tests were conducted by imposing constraints on the coefficients in the upper panel of Table 4 and testing the deterioration in model fit using the chi-square difference test. These constraints were tested separately for leadership, communication, and planning and organizing. For level predicting level, the four coefficients for each dimension in the upper panel of Table 4 were constrained to be equal. For congruence predicting level, the four coefficients were constrained to be opposite across the columns and equal across the rows. For level predicting congruence, the four coefficients were constrained to be equal across the columns and opposite across the rows. Finally, for congruence predicting congruence, the four coefficients were constrained to be opposite across the columns and opposite across the rows. These patterns are illustrated by Cases 2, 4, 6, and 8, respectively, in the columns of Table 3 reporting results for X_1 and X_2 as predictors of Y_1 and Y_2.

Table 5 shows that, for leadership, the constraints for congruence predicting level were not rejected. This result is consistent with the pattern of coefficients for leadership in the upper panel of Table 4, for which the coefficients on manager perceptions of leadership

Table 4
Coefficient Estimates for Cheung (2007) Data

Manager and Supervisor Perceptions as Predictors and Outcomes

	Leadership		Communication		Planning & Organizing	
Customer service	Manager	Supervisor	Manager	Supervisor	Manager	Supervisor
Manager	0.40*	−0.23	0.43*	0.12	0.10	0.14
Supervisor	0.04	−0.27	−0.12	1.18**	0.22	0.15

Level and Congruence as Predictors and Outcomes

	Leadership		Communication		Planning & Organizing	
Customer service	Level	Congruence	Level	Congruence	Level	Congruence
Level	−0.03	−0.24	0.81**	0.25	0.31*	−0.01
Congruence	−0.39	0.16	0.52	0.81**	0.14	−0.06

Note: $N = 220$. Table entries are unstandardized coefficients. Coefficients in the upper panel were estimated from a structural equation model that specified manager and supervisor perceptions of leadership, communication, and planning and organizing as latent exogenous variables and manager and supervisor perceptions of customer service as latent endogenous variables. Coefficients in the lower panel were computed and tested using the additional parameters feature of LISREL.

Table 5
Chi-Square Difference Tests for Cheung (2007) Data

Coefficient Pattern	Leadership	Communication	Planning & Organizing
Level predicting level	8.69*	19.42**	0.71
Congruence predicting level	4.21	25.25**	7.48
Level predicting congruence	8.75*	46.43**	6.96
Congruence predicting congruence	9.03*	140.58**	6.92

Note: $N = 220$. Table entries are chi-square difference tests for constraints associated with each coefficient pattern listed in the left column. Each test involved three constraints and therefore had 3 degrees of freedom. For level predicting level, the four coefficients for each dimension in the upper panel of Table 4 were constrained to be equal. For congruence predicting level, the four coefficients were constrained to be opposite across the columns and equal across the rows. For level predicting congruence, the four coefficients were constrained to be equal across the columns and opposite across the rows. Finally, for congruence predicting congruence, the four coefficients were constrained to be opposite across the columns and opposite across the rows. These patterns are illustrated by Cases 2, 4, 6, and 8, respectively, in the columns of Table 3 reporting results for X_1 and X_2 as predictors of Y_1 and Y_2.
$^{*}p < .05$. $^{**}p < .01$.

were both positive and the coefficients on supervisor perceptions of leadership were both negative. However, only one of the four coefficients was significant, meaning that the coefficients for leadership should not be interpreted in terms of congruence predicting level but instead as a single relationship between manager perceptions of leadership and customer service. For communication, all four patterns of coefficients were rejected. Finally, for planning and organizing, none of the patterns was rejected, which is symptomatic of the fact that none of the four coefficients for planning and organizing differed significantly from zero.

The scarcity of significant relationships in Table 4 was striking given that, from a substantive perspective, perceptions of leadership, communication, planning and organizing, and customer service from the same source should be related. These relationships were further examined by conducting a confirmatory factor analysis of the eight manager and supervisor factors. Results revealed that the correlations among the four manager factors were high, averaging .88 and ranging from .84 to .92. The correlations among the four supervisor factors were also high, averaging .80 and ranging from .72 to .89. Hence, the absence of significant relationships in Table 4 was due to high correlations among the leadership, communication, planning and organizing factors used as predictors, which introduced multicollinearity into the structural equations of the model. Moreover, each of the eight factors failed to achieve discriminant validity with least one other factor, as evidenced by correlations that included 1.0 in their 95% confidence intervals. The lack of discriminant validity among these factors undermines the utility of the Cheung (2007) data for illustrating the LCM and partly explains the anomalous results reported here and by Cheung.

Future Directions for Latent Variable Modeling in Congruence Research

The preceding analyses show that the LCM conceals information needed to test level and congruence hypotheses and yields results that invite erroneous conclusions. Nonetheless, the LCM has two important strengths in that it takes measurement error into account and permits tests of measurement equivalence for the component variables. Of course, these strengths are not unique to the LCM, because they derive from the use of structural equation modeling with latent variables, not the use of level and congruence as second-order factors. These factors were dropped from the model used to reanalyze the Cheung (2007) data, yet this model controlled for measurement error and included the measurement invariance constraints embedded in the LCM. Hence, moving to structural equation modeling with latent variables is an important and logical step for congruence research, but this step does not require the LCM.

Other approaches to incorporating structural equation modeling into congruence research are available. The linear model used here to reanalyze the Cheung (2007) data can be applied to linear congruence relationships, as when satisfaction increases as rewards approach needs and continues to increase as rewards exceed needs. However, the linear model cannot verify that the hypothesized relationship is actually linear rather than curvilinear, a conceptually plausible alternative in many domains of congruence research (Edwards, Caplan, & Harrison, 1998; Locke, 1976; Rice, McFarlin, Hunt, & Near, 1985). Moreover, linear models are insufficient when congruence is conceptualized as the fit, similarity, match, or agreement between two constructs (Chatman, 1989; Dawis, 1992; Edwards, 1994; Judge & Ferris, 1992; Kristof, 1996; Muchinsky & Monahan, 1987). For example, person-organization fit is defined as the match between person and organization attributes (e.g., values) and is hypothesized to produce various positive outcomes, such as job satisfaction and organizational commitment (Kristof-Brown et al., 2005). The notion that fit generates positive outcomes implies a curvilinear (i.e., inverted-U) relationship, such that outcomes are maximized when the person and organization are equal and decrease as the person and organization differ in either direction.

Curvilinear relationships that characterize much congruence research require analytical approaches that go beyond linear structural equation models. One approach is to translate the quadratic regression equation typically used in polynomial regression (Edwards & Parry, 1993) into a quadratic structural equation with latent variables (Edwards & Kim, 2002). This approach requires extending methods for testing interactions in structural equation modeling (Cortina, Chen, & Dunlap, 2001; Jöreskog, 1998; Li et al., 1998) to include curve components for the two variables involved in the interaction (Cohen, 1978; Cortina, 1993; MacCallum & Mar, 1995). Like the LCM, quadratic structural equation modeling takes measurement error into account and allows tests of measurement equivalence. However, unlike the LCM, quadratic structural equation modeling accommodates curvilinear relationships. Furthermore, results from quadratic structural equations can be used to conduct response surface analyses (Edwards, 2002; Edwards & Parry, 1993), yielding rigorous and comprehensive tests of congruence hypotheses in terms of latent variables.

Quadratic structural equations treat congruence as a predictor. When congruence is an outcome, multivariate regression procedures outlined by Edwards (1995) can be applied to multiple-group structural equation models in which groups are defined based on whether scores on one latent component variable are greater than or less than the other. Latent variable scores can be obtained using procedures described by Jöreskog (2000), such that the classification of cases into subgroups takes into account measurement error in the component variables. Models for each subgroup are linear, such that their specification and estimation are straightforward, and conditions for assessing congruence described by Edwards (1995) can be directly applied.

Level and Congruence as Constructs

The procedures recommended in this article enable the study of congruence with latent variable structural equation modeling without creating variables that signify level or congruence. This notion might create objections among researchers who view congruence as distinct from its components (Cheung, 2007; Tisak & Smith, 1994). Although congruence is distinct from either component taken separately, it is not distinct from the two components considered jointly. This fact is evident in Equation 4, which shows that congruence is defined as the difference between the component variables. As such, any meaning ascribed to congruence cannot go beyond the two component variables that define congruence. This point also applies to level, which is defined as the mean of the component variables, as indicated by Equation 3. Defined in this manner, congruence and level are redundant with their component variables, and any attempt to distinguish congruence and level from their components is futile. For instance, a basic prerequisite for establishing the unique existence of a construct is discriminant validity, such that the construct does not overlap with other similar constructs (Campbell & Fiske, 1959). Because level and congruence are defined in terms of their components, the multiple correlations relating the components to level and congruence are 1.00, and the matrix of correlations among level, congruence, and the two component variables is singular, such that four distinct factors cannot be extracted.

Rather than conceptualizing congruence and level as constructs, they should be viewed as statements about the relative standing of the component variables to one another. For instance, if congruence is conceptualized as the fit, match, or similarity between two component variables (Edwards, 1994), then congruence is indicated when the component variables are equal. Saying that the component variables are equal does not invoke some new construct, no more than saying that a single variable equals some low or high score creates constructs we would call "low" or "high." Likewise, hypotheses concerning the effects of congruence can be viewed as statements about the joint effects of the component variables. For instance, predicting that congruence leads to positive outcomes is tantamount to predicting that outcomes are maximized when the component variables are equal. Predicting a congruence effect does not invoke a "congruence" construct any more than predicting an interaction calls forth an "interaction" construct. Similar arguments apply to level, which can be conceptualized in terms of the component variables taken jointly.

Some researchers operationalize congruence not by subtracting component variables, as in Equation 4, but instead by asking respondents to directly report the difference or similarity between the component variables (e.g., Cable & DeRue, 2002). When congruence is measured in this manner, it is arguably distinct from the component measures taken jointly, given that comparative judgments are susceptible to influences other than the elements being compared (Chambers & Windschitl, 2004; Mussweiler, 2003; Tversky, 1977). The mapping of component variables onto judgments of their difference and congruence is worth studying in its own right (Edwards, Cable, Williamson, Lambert, & Shipp, 2006), but this research is meaningful only when congruence is operationalized not by subtracting component variables, as in Equation 4, but by measuring perceived differences and congruence directly.

Conclusion

Congruence research has been marked by various methodological developments, such as the movement from difference scores and profile similarity indices to polynomial regression, and an important next step is to translate polynomial regression into structural equation models with latent variables (Edwards & Kim, 2002). The LCM proposed by Cheung (2007) capitalizes on the advantages of structural equation modeling but takes a step backward by focusing analyses on the mean and difference between components variables. This article highlights the problems associated with the LCM and shows how the questions that the LCM is intended to address can be answered using structural equation models with latent component variables. Additional work is needed to move beyond linear models to incorporate quadratic equations into structural equation models (Edwards & Kim, 2002), which are required for testing theories in congruence research.

Appendix A
LISREL Syntax for Reanalysis of Cheung (2007) Data

The following LISREL syntax revises the syntax reported by Cheung (2007) by dropping the second-order level and congruence factors and adding 12 additional parameters to compute the coefficients that would be produced by the level and congruence factors. Below the syntax are lines of code that impose constraints implied by level and congruence predicting level and congruence. Each set of constraints can be tested by inserting the relevant lines of code above the OU line.

```
Leadership and Teams: Modification of Cheung (2007) syntax
DA NI=24 NO=220
LA
SlfL1 SlfL2 SlfL3 SlfC1 SlfC2 SlfC3
SlfPO1 SlfPO2 SlfPO3 SlfCS1 SlfCS2 SlfCS3
SupL1 SupL2 SupL3 SupC1 SupC2 SupC3
SupPO1 SupPO2 SupPO3 SupCS1 SupCS2 SupCS3
CM=CSB.CM RE
ME=CSB.ME RE
SELECT
SlfCS1 SlfCS2 SlfCS3 SupCS1 SupCS2 SupCS3
SlfL1 SlfL2 SlfL3 SupL1 SupL2 SupL3
SlfC1 SlfC2 SlfC3 SupC1 SupC2 SupC3
SlfPO1 SlfPO2 SlfPO3 SupPO1 SupPO2 SupPO3/
MO NY=6 NE=2 LY=FI TY=FI TE=FR NX=18 NK=6 LX=FI TX=FI TD=FI TD = FR C
PS=SY,FR PS = SY,FR AL=FR KA=FR GA=FR AP=12
! Measurement model for leadership
VA 1 LX(1,1) LX(4,2)
FR LX(2,1) LX(3,1) LX(5,2) LX(6,2)
FR TX 2 TX 3 TX 5 TX 6
EQ LX(2,1) LX(5,2) /* Syntax for metric equivalence
EQ LX(3,1) LX(6,2) /* Syntax for metric equivalence
EQ TX 2 TX 5 /* Syntax for scalar equivalence
EQ TX 3 TX 6 /* Syntax for scalar equivalence
! Measurement model for communication
VA 1 LX(7,3) LX(10,4)
FR LX(8,3) LX(9,3) LX(11,4) LX(12,4)
FR TX 8 TX 9 TX 11 TX 12
EQ LX(8,3) LX(11,4) /* Syntax for metric equivalence
EQ LX(9,3) LX(12,4) /* Syntax for metric equivalence
EQ TX 8 TX 11 /* Syntax for scalar equivalence
!EQ TX 9 TX 12 /* Item with nonequivalent intercepts
! Measurement model for planning and organizing
VA 1 LX(13,5) LX(16,6)
FR LX(14,5) LX(15,5) LX(17,6) LX(18,6)
FR TX 14 TX 15 TX 17 TX 18
```

```
EQ LX(14,5) LX(17,6) /* Syntax for metric equivalence
EQ LX(15,5) LX(18,6) /* Syntax for metric equivalence
!EQ TX 14 TX 17 /* Item with nonequivalent intercepts
EQ TX 15 TX 18 /* Syntax for scalar equivalence
! Measurement model for customer service
VA 1 LY(1,1) LY(4,2)
FR LY(2,1) LY(3,1) LY(5,2) LY(6,2)
FR TY 2 TY 3 TY 5 TY 6
EQ LY(2,1) LY(5,2) /* Syntax for metric equivalence
EQ LY(3,1) LY(6,2) /* Syntax for metric equivalence
EQ TY 2 TY 5 /* Syntax for scalar equivalence
EQ TY 3 TY 6 /* Syntax for scalar equivalence
LK
SlfLdr SupLdr SlfCom SupCom SlfPO SupPO
LE
SlfCust SupCus
! Coefficients for level predicting level
CO PA(1)=.5*GA(1,1)+.5*GA(1,2)+.5*GA(2,1)+.5*GA(2,2)
CO PA(2)=.5*GA(1,3)+.5*GA(1,4)+.5*GA(2,3)+.5*GA(2,4)
CO PA(3)=.5*GA(1,5)+.5*GA(1,6)+.5*GA(2,5)+.5*GA(2,6)
! Coefficients for congruence predicting level
CO PA(4)=-.25*GA(1,1)+.25*GA(1,2)-.25*GA(2,1)+.25*GA(2,2)
CO PA(5)=-.25*GA(1,3)+.25*GA(1,4)-.25*GA(2,3)+.25*GA(2,4)
CO PA(6)=-.25*GA(1,5)+.25*GA(1,6)-.25*GA(2,5)+.25*GA(2,6)
! Coefficients for level predicting congruence
CO PA(7)=-1*GA(1,1)-GA(1,2)+GA(2,1)+GA(2,2)
CO PA(8)=-1*GA(1,3)-GA(1,4)+GA(2,3)+GA(2,4)
CO PA(9)=-1*GA(1,5)-GA(1,6)+GA(2,5)+GA(2,6)
! Coefficients for congruence predicting congruence
CO PA(10)=.5*GA(1,1)-.5*GA(1,2)-.5*GA(2,1)+.5*GA(2,2)
CO PA(11)=.5*GA(1,3)-.5*GA(1,4)-.5*GA(2,3)+.5*GA(2,4)
CO PA(12)=.5*GA(1,5)-.5*GA(1,6)-.5*GA(2,5)+.5*GA(2,6)
OU AD=OFF ND=4
! Constraints for level predicting level
! Leadership
CO GA(1,2)=GA(1,1)
CO GA(2,1)=GA(1,1)
CO GA(2,2)=GA(1,1)
! Constraints for level predicting level
! Communication
CO GA(1,4)=GA(1,3)
CO GA(2,3)=GA(1,3)
CO GA(2,4)=GA(1,3)
! Constraints for level predicting level
! Planning and organizing
CO GA(1,6)=GA(1,5)
CO GA(2,5)=GA(1,5)
CO GA(2,6)=GA(1,5)
```

```
! Constraints for congruence predicting level
! Leadership
CO GA(1,2)=−1*GA(1,1)
CO GA(2,1)=GA(1,1)
CO GA(2,2)=−1*GA(1,1)
! Constraints for congruence predicting level
! Communication
CO GA(1,4)=−1*GA(1,3)
CO GA(2,3)=GA(1,3)
CO GA(2,4)=−1*GA(1,3)
! Constraints for congruence predicting level
! Planning and organizing
CO GA(1,6)=−1*GA(1,5)
CO GA(2,5)=GA(1,5)
CO GA(2,6)=−1*GA(1,5)
! Constraints for level predicting congruence
! Leadership
CO GA(1,2)=GA(1,1)
CO GA(2,1)=−1*GA(1,1)
CO GA(2,2)=−1*GA(1,1)
! Constraints for level predicting congruence
! Communication
CO GA(1,4)=GA(1,3)
CO GA(2,3)=−1*GA(1,3)
CO GA(2,4)=−1*GA(1,3)
! Constraints for level predicting congruence
! Planning and organizing
CO GA(1,6)=GA(1,5)
CO GA(2,5)=−1*GA(1,5)
CO GA(2,6)=−1*GA(1,5)
! Constraints for congruence predicting congruence
! Leadership
CO GA(1,2)=−1*GA(1,1)
CO GA(2,1)=−1*GA(1,1)
CO GA(2,2)=GA(1,1)
! Constraints for congruence predicting congruence
! Communication
CO GA(1,4)=−1*GA(1,3)
CO GA(2,3)=−1*GA(1,3)
CO GA(2,4)=GA(1,3)
! Constraints for congruence predicting congruence
! Planning and organizing
CO GA(1,6)=−1*GA(1,5)
CO GA(2,5)=−1*GA(1,5)
CO GA(2,6)=GA(1,5)
```

Appendix B
Solving for Coefficients Relating L_X and C_X to L_Y and C_Y in Terms of b_{11}, b_{12}, b_{21}, and b_{22}

To write the coefficients relating L_X and C_X to L_Y and C_Y in terms of b_{11}, b_{12}, b_{21}, and b_{22}, we begin by solving Equations 22, 23, 24, and 25 for X_1, X_2, Y_1, and Y_2. First, we solve Equations 22 and 23 for X_1 and X_2, which yields:

$$X_1 = L_X - .5C_X \quad \text{(A1)}$$
$$X_2 = L_X + .5C_X. \quad \text{(A2)}$$

Next, we solve Equations 24 and 25 for Y_1 and Y_2, which produce:

$$Y_1 = L_Y - .5C_Y \quad \text{(A3)}$$
$$Y_2 = L_Y + .5C_Y. \quad \text{(A4)}$$

We then substitute these expressions into Equations 32 and 33,

$$L_Y - .5C_Y = b_{10} + b_{11}(L_X - .5C_X) + b_{12}(L_X + .5C_X) + e_1 \quad \text{(A5)}$$
$$L_Y + .5C_Y = b_{20} + b_{21}(L_X - .5C_X) + b_{22}(L_X + .5C_X) + e_2. \quad \text{(A6)}$$

Adding Equations A5 and A6 and simplifying gives the equation for L_Y:

$$\begin{aligned}
L_Y - .5C_Y + L_Y + .5C_Y &= b_{10} + b_{11}(L_X - .5C_X) + b_{12}(L_X + .5C_X) + e_1 \\
&\quad + b_{20} + b_{21}(L_X - .5C_X) + b_{22}(L_X + .5C_X) + e_2 \\
2L_Y &= b_{10} + b_{20} + b_{11}L_X - .5b_{11}C_X + b_{12}L_X + .5b_{12}C_X \\
&\quad + b_{21}L_X - .5b_{21}C_X + b_{22}L_X + .5b_{22}C_X + e_1 + e_2 \\
2LY &= b_{10} + b_{20} + (b_{11} + b_{12} + b_{21} + b_{22})L_X \\
&\quad + .5(b_{12} - b_{11} + b_{22} - b_{21})C_X + e_1 + e_2 \\
L_Y &= .5(b_{10} + b_{20}) + .5(b_{11} + b_{12} + b_{21} + b_{22})L_X \\
&\quad + .25(b_{12} - b_{11} + b_{22} - b_{21})C_X + .5(e_1 + e_2). \quad \text{(A7)}
\end{aligned}$$

Subtracting Equation A5 from Equation A6 and simplifying gives the equation for C_Y:

$$\begin{aligned}
L_Y + .5C_Y - L_Y + .5C_Y &= b_{20} - b_{10} + b_{21}(L_X - .5C_X) - b_{11}(L_X - .5C_X) \\
&\quad + b_{22}(L_X + .5C_X) - b_{12}(L_X + .5C_X) + e_2 - e_1 \\
C_Y &= b_{20} - b_{10} + b_{21}L_X - .5b_{21}C_X - b_{11}L_X + .5b_{11}C_X \\
&\quad + b_{22}L_X + .5b_{22}C_X - b_{12}L_X - .5b_{12}C_X + e_2 - e_1 \\
C_Y &= b_{20} - b_{10} + (b_{21} - b_{11} + b_{22} - b_{12})L_X \\
&\quad + .5(b_{11} - b_{12} - b_{21} + b_{22})C_X + e_2 - e_1 \quad \text{(A8)}
\end{aligned}$$

Notes

1. The erroneous interpretation yielded by Equation 6 can also be seen by noting that, in general, regression coefficients, such as a_1, indicate the effect of the associated predictor holding all other predictors constant. However, this interpretation does not apply to Equation 6, in that a change in the term associated with a_1 also entails a change in the term associated with a_2, given that Y_1 and Y_2 appear in both terms. Thus, the conclusion that a_1 implies equal effects of Y_1 and Y_2 is correct only when $a_2 = 0$. This perspective applies to the erroneous interpretations yielded by other equations that use L and C as predictors. I am indebted to an anonymous reviewer for articulating this perspective.

2. In total, the five levels of b_1 and nine levels of b_2 used here could yield 45 possible combinations. However, the nine combinations selected for illustration are sufficient to demonstrate the problems that result from using L and C as predictors. Examples presented later in this article also use subsets of the possible combinations of parameters chosen for illustration, thereby demonstrating problems with L and C while keeping the illustrations manageable in size.

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