Multilevel Latent Polynomial Regression for Modeling (In)Congruence across Organizational Groups: The Case of Organizational Culture Research

Michael J. Zyphur
Department of Management and Marketing
University of Melbourne
Victoria 3010
Australia
Phone: +61 3 9035 5826
Email: mzyphur@unimelb.edu.au

Raymond F. Zammuto
The Business School
University of Colorado, Denver
Denver CO 80202
Phone: 301 836 6252
Email: ray.zammuto@gmail.com

Zhen Zhang
W. P. Carey School of Business
Department of Management
Arizona State University
PO BOX 874006
Tempe, AZ 85287-4006
Phone: 480-965-5560
Email: zhen.zhang@asu.edu

Author's note*: Please address all correspondence regarding organization culture to Raymond F. Zammuto (ray.zammuto@gmail.com); please address all correspondence regarding the multilevel method to Michael J. Zyphur (mzyphur@unimelb.edu.au). The authors would like to express their appreciation to Stephen Shortell for access to the data, and to Herman Aguinis, Neal Ashkanasy, Victor Callan, Michael Christian, Noah Eisnekraft, Angelo Kinicki, Wendong Li, Joanne Martin, Scott Seibert, Stephen Shortell, and April Wright for their comments on earlier drafts.*

Key words: *Organizational culture, multilevel structural equation modeling, multilevel latent polynomial regression, latent moderated structural equations, multilevel moderation*

Abstract

This paper addresses (in)congruence across different kinds of organizational respondents or ‘organizational groups’—such as managers versus non-managers or women versus men—and the effects of congruence on organizational outcomes. We introduce a novel multilevel latent polynomial regression model (MLPM) that treats standings of organizational groups as latent ‘random intercepts’ at the organization level, while subjecting these to latent interactions that enable response surface modeling to test congruence hypotheses. We focus on the case of organizational culture research, which usually samples managers and excludes non-managers. Re-analyzing data from 67 hospitals with 6,731 managers and non-managers, we find that non-managers perceive their organizations’ cultures as less humanistic and innovative and more controlling than managers, and less congruence between managers and non-managers in these perceptions is associated with lower levels of quality improvement in organizations. Our results call into question the validity of findings from organizational culture and other research that tends to sample one organizational group to the exclusion of others. We discuss our findings and the MLPM, which can be extended to estimate latent interactions for tests of multilevel moderation/interactions.

Keywords: Organizational culture, Congruence, Multilevel latent polynomial regression, Multilevel structural equation modeling, Multilevel moderation

Multilevel Latent Polynomial Regression for Modeling

(In)Congruence across Organizational Groups:

The Case of Organizational Culture Research

Statistics are often described on representational terms, with samples meant to represent populations and/or phenomena that exist external to the research process (e.g., Shadish, Cook, & Campbell, 2002). Although many researchers espouse this narrative, representativeness is often lacking in organizational research (Short, Ketchen, & Palmer, 2002). At times this is acceptable, as in case studies and ‘key informant’ designs (Eisenhardt & Graebner, 2007; Kumar, Stern, & Anderson, 1993). However, at other times researchers undermine representativeness by sampling a single kind of respondent in organizations, or an ‘organizational group’, in order to represent phenomena that may not be shared across these groups, such as the perceptions of managers versus non-managers. In turn, questions arise as to the degree of (in)congruence across different organizational groups and the effects of this (in)congruence on organizational outcomes.

Consider these examples: 1) research on high-performance work systems usually surveys only managers to assess the existence of these systems, even though non-managers have been shown to have different views on their implementation that uniquely predict performance (Liao, Toya, Lepak, & Hong, 2009); 2) strategic management research often focuses on only managers when examining organizational strategy (e.g., Finkelstein & Hambrick, 1996), even though the doing of ‘strategy as practice’ involves non-managers who have unique perspectives and effects on implementation (see work in Golsorkhi, Rouleau, Seidl, & Vaara, 2010); 3) leader-member exchange research is based on theory about relationships, but usually only leaders or followers are sampled even though these respondents often do not agree (Sin, Nahrgang, & Morgeson, 2009), their perceptions are not highly correlated (Gerstner & Day, 1997), and such misalignment negatively impacts work outcomes (Matta, Scott, Koopman, & Conlon, in press).

Our paper addresses congruence across organizational groups that differ with respect to some relevant attribute(s). To help researchers conceptualize and test for the existence and effects of congruence across these groups, we offer a novel multilevel latent polynomial regression model (MLPM) with data descriptions and Mplus program code in Appendices A, B, and C. The MLPM simultaneously estimates the standings of organizations and organizational groups as latent 'random intercepts' that account for sampling error. In turn, estimating latent interactions among the groups' standings allows constructing a bias-corrected response surface that describes the relationship among congruence and organizational outcomes. This approach to latent interactions among random intercepts allows testing for multilevel moderation/interactions and non-linear relationships more generally, but we focus on response surface modeling to assess the existence and effects of congruence across organizational groups. As a whole, our method synthesizes approaches to multilevel structural equation modeling (e.g., Preacher, Zyphur, & Zhang, 2010), latent interactions in structural equation models (e.g., Klein & Moosbruger, 2000), and response surface methods using polynomial regression in single-level (e.g., Edwards, 1994) or multilevel models (e.g., Jansen & Kristof-Brown, 2005).

Although we could illustrate the MLPM with various examples for various groups—such as women versus men or different racial groups as in organizational demography research—we treat an area of study plagued by non-representative research with two common groups: survey-based organizational culture research that usually samples managers and excludes non-managers. Organizational culture is commonly defined as emerging from the *shared* assumptions, values, and beliefs among an organization's members (O'Reilly, 1989; Schein, 2004). Yet, examining the studies in Hartnell, Ou, and Kinicki's (2011) recent meta-analysis of the organizational culture-organizational effectiveness relationship shows that 70% of the studies sampled only managers. Thus, we target this research for our analysis because it is almost always focused on *cultural content*—a culture's values, beliefs, and assumptions—with little regard for what we call *cultural congruence*—the similarity of cultural content across organizational groups.

Using the example of organizational culture and managers versus non-managers, in what follows we describe the problem of congruence as being related to both grand-mean differences across sets of organizational groups as well as degrees of congruence in any given organization and how this relates to organizational outcomes. Based on past research and theory we show how to deploy the MLPM and interpret results by offering hypotheses that allow testing our assertions about cultural incongruence relative to one indicator of organizational effectiveness (as in Hartnell et al., 2011): *management innovation*, defined as the generation and implementation of a new management practice, process, structure, or technique (Birkinshaw, Hamel, & Mol, 2008).

We test our hypotheses and illustrate the MLPM with data from Shortell et al.'s (1995) study of the relationship between organizational culture and a common management innovation: total quality management. The MLPM extends their conclusions by showing that non-managers perceive organizational culture as more controlling and task-oriented than do managers, and that these incongruent perceptions have a negative relationship with the implementation of quality improvement practices (*QI*). Along with post-hoc analyses that illustrate how to interrogate MLPM results, our work calls into question the conclusions of most survey-based organizational culture research as well as a vast array of similar research that lacks representativeness and fails to test for the existence and the effects of congruence across organizational groups. We conclude by discussing the implications of our findings and the MLPM.

We first treat organizational culture research in a way that helps illustrate how to map theory and hypotheses onto the MLPM, and the unique response surface method that it allows. In brief, researchers can hypothesize/test: 1) the effects of a substantive variable on organizational outcomes while holding (in)congruence constant (the effect of 'cultural content' in Hypothesis 1 below); 2) grand-mean differences between organizational groups along a substantive variable (grand-mean differences between manager and non-manager culture perceptions as Hypothesis 2 below); and 3) effects of (in)congruence across organizational groups on organizational outcomes (the effect of (in)congruence in manager and non-manager culture perceptions on quality implementation at the organizational level as Hypothesis 3 below).

Cultural Content, Congruence, and Management Innovation

Although scholars have approached culture research from multiple perspectives, we focus on the Competing Values Framework (CVF), which has provided the conceptual grounding for much empirical research on organizational culture (Cameron & Quinn, 2006; Ostroff, Kinicki, & Muhammad, 2012), and is the cultural template used in Shortell et al.'s (1995) study. Given our interest in manager and non-manager perceptions of cultural content, we briefly review the CVF before discussing the impact of cultural content and congruence on management innovation.

Cultural Content: The Competing Values Framework

The CVF proposes that shared values and beliefs underlying organizational culture can be distinguished on two axes: preference for structuring and focus of attention (Quinn, 1988). The *preference for structuring* axis is anchored by end-points of flexibility and control, as in O'Reilly and Chatman's (1996) distinction of social versus formal control. A *flexibility* end-point focuses on social control, wherein compliance is gained by norms arising in internalized beliefs, peer pressure, and participation and commitment. A *control* end-point indicates gaining compliance by formal control mechanisms, such as rules, policies, procedures, financial planning systems, and budgets. The *focus of attention* axis is anchored by end-points of internal focus and external focus. On the *internal* end-point, attention is focused in an organization on its internal dynamics and the maintenance of its socio-technical system. On the *external* end-point, attention is focused outside an organization on the demands of its environment and its ability to compete within it.

The intersection of these two axes creates four quadrants that represent competing values of desired organizational ends and means for attaining them (Quinn, 1988). The *internal process quadrant* (control/internal focus) values ends of stability and control by means of measurement, documentation, and information management. Organizations emphasizing this quadrant are often bureaucratic, relying on practices like top-down decision making and extensive rules and policies to coordinate and control activities. A *human relations quadrant* (flexible/internal focus) values ends of commitment and morale attained by means like discussion, participation and openness. Organizations with these values often have participative decision-making, investments in human resource development, and long tenure for members. A *rational goal quadrant* (control/external focus) values ends of task accomplishment and productivity attained by means of planning and goal setting. An example is Hammer and Champy's (1993) vision of reengineering as designing processes to create outcomes valued by customers that also create productivity improvements. Finally, the *open systems quadrant* (flexibility/external focus) values ends of growth and resource acquisition by innovation and adaptation. Often seen as innovative and entrepreneurial, organizations emphasizing this quadrant encourage risk-taking, empowerment and learning.

Several papers using the CVF to study the culture-management innovation relationship find that cultural content emphasizing the human relations and open systems quadrants is more conducive to management innovation than that emphasizing internal process and rational goal quadrants. For example: Zammuto and Krakower (1991) and Burton, Lauridsen, and Obel (2004) found that the human relations and open systems quadrants were positively related to perceived equity of rewards, leader credibility and trust, conditions that assist implementing management innovations; Chang and Weibe (1996) showed that an emphasis on the human relations and open systems quadrants was ideal for implementing TQM; and Jones, Jimmieson, and Griffiths (2005) report that the human relations quadrant is positively associated with readiness to change in the implementation of human resource systems. Consistent with this literature and Shortell et al.'s (1995) finding that cultural content emphasizing the human relations and open systems quadrants predicted quality improvement practices, we expect our reanalysis will show that:

> *Hypothesis 1:* Cultural content emphasizing the human relations and open systems quadrants (the flexibility end of the preference for structuring axis) will be positively related to management innovation.

Although this relationship has been demonstrated in previous studies, it is included here because later it will help illustrate the MLPM and the hypotheses that congruence research often test, which include effects along the 'line of congruence' (i.e., Hypothesis 1's effect of cultural content, as we later describe). Indeed, studies of the culture-performance relationship typically offer similar arguments to ours when hypothesizing a relationship between cultural values and performance. However, this argument ignores the possibility and implications of cultural (in)congruence. We now explain why discrepancies in manager and non-manager perceptions of cultural content may exist and why such differences are important to the culture-management innovation relationship.

Cultural Congruence: Hierarchy's Effect on the Perception of Cultural Content

Cultural congruence refers to the degree that groups in an organization perceive similar cultural content and associated practices, processes, and outcomes. Here, we argue that hierarchy can lead to divergent perceptions of cultural content due to variations in tasks and values at different organizational levels (Schein, 2004; Stackman, Pinder, & O'Connor, 2000). These differences are often pronounced across managers and non-managers, with managers facing more uncertainty in tasks compared to people at lower levels in an organization (Trice & Beyer, 1993). Managers are also more likely to experience organizational identity as an outgrowth of an organization's vision and strategy, while non-managers view identity as grounded in day-to-day realities of work (Corley, 2004). Thus, although managers' perceptions of cultural content are grounded in their experiences, these may not be shared by non-managers (O'Reilly, 1989).

Research on hierarchical differentiation in organizations notes that differences in roles and responsibilities can result in variation in the realities of managers and non-managers (Evan, 1977) due to diverging environments (Tannenbaum et al., 1974). As Tannenbaum and Rozgonyi note, "the organizational world of persons at upper levels of the work organization is predictably different—physically, socially, and psychologically—from that of persons at lower levels. At the top more than at the bottom, it is a world in which persons have authority and exercise influence. The world at the top is also more interesting and 'enriching,' more congenial and comfortable, more satisfying, and less alienating" (1986, p. 233). Thus, we expect that, across all groups of manager and non-managers, perceptions of cultural content will diverge:

Hypothesis 2: Managers will, on average, perceive their culture's content as being more humanistic and innovative and less controlling and task-focused than non-managers.

Research on person-organization fit suggests that such differences can have a substantial effect on an organization because perceptual congruence increases positive attitudes and organizational outcomes. For instance: Ostroff et al. (2005) showed that congruence of non-managers' and managers' perceptions of organizational values is positively related to non-managers' satisfaction and commitment; Gibson, Cooper, and Conger (2009) found that team performance is highest when there are congruent perceptions about task accomplishment among leaders and members; and Edwards and Cable (2009) reported improved trust and communication with increased congruence between individual and organizational values.

Research on trust shows that congruence increases social integration because shared values build trust (Lewicki, McAllister, & Bies, 1998; Sitkin & Roth, 1993), which enhances cooperative behavior (Axelrod, 1984; Jones & George, 1998). Specifically, shared values are positively associated with trust among managers and non-managers (Burke, Sims, Lazzara, & Salas, 2007; Fulmer & Gelfand, 2012; Gillespie & Mann, 2004). In turn, trust in management increases non-managers' positive attitudes toward change (Devos, Buelens, & Bouckenooghe, 2007), readiness for change (Armenakis, Harris, & Mossholder, 1993), and negatively relates to resistance to change (DeCelles, Tesluk, & Taxman, 2013; Oreg & Sverdlik, 2011). Trust also increases the legitimacy of explanations for and acceptance of change, which positively relate to implementation success (Dirks & Ferrin, 2001; Hill, Seo, Kang, & Taylor, 2012; Rousseau & Tijoriwala, 1999; Sonpar, Handelman, & Dastmalchian, 2009). Thus higher levels of trust, which is enhanced by congruence, will be conducive to the successful implementation of management innovations. In turn, we hypothesize that:

Hypothesis 3: As congruence between manager and non-manager perceptions of cultural content increases, the implementation of management innovation will increase.

In sum, past research shows that cultural content is positively related to management innovation when values and practices associated with the CVF's human relations and open systems quadrants are emphasized (Hypothesis 1). We argue that because of differences created by hierarchical position, on average, managers will view cultural content as more humanistic and innovative, and less controlling and task-focused than non-managers (Hypothesis 2). We also propose that increasingly congruent perceptions of cultural content across managers and non-managers will be associated with implementing management innovation (Hypothesis 3). Before continuing, it is notable that the mean differences described in Hypothesis 2 are grand-means based on all organizations pooled together. Thus, support (or lack of support) for Hypothesis 2 does not preclude the possibility of finding a high level (or low level) of cultural congruence in particular organizations (i.e., Hypothesis 3).

Multilevel Latent Polynomial Regression Model (MLPM)

The MLPM generalizes polynomial regression as described in Edwards and Parry (1993) and Edwards (1994), which estimates a joint relationship among three variables. The result is a response surface showing how two predictors (e.g., cultural content for managers and non-managers) relate to an outcome (e.g., quality implementation) in order to test congruence hypotheses. The required polynomial regression model with our variables can be shown as

$$QI = b_1 + b_2 CC_M + b_3 CC_{NM} + b_4 CC_M^2 + b_5 CC_M CC_{NM} + b_6 CC_{NM}^2 + e, \tag{1}$$

wherein QI is quality implementation for an organization, CC_M is cultural content for all managers in an organization, CC_{NM} is cultural content for all non-managers in an organization, squared terms allow non-linearity in the relationship between cultural content and QI, and the product term allows estimating the joint effect of CC_M and CC_{NM} on QI. The standing of any organizational groups along any variable could be substituted in Equation 1 (e.g., perceptions of fairness in women versus men or ethnic minorities versus whites), and any outcome could be substituted as well (e.g., turnover or organizational commitment). In all cases, the point would be to use estimates of the βs to construct statistics that describe a response surface that shows the relationship among the groups' standings and the outcome of interest at the organizational level.

However, the problem with Equation 1 when using individual data is that variables like CC_M, CC_{NM}, and *QI* are not measured at the organizational level (also referred to as the 'cluster', 'aggregate' or merely 'higher' level). Although computing means in such cases is common (e.g., Gibson et al., 2009), this causes bias in the presence of sampling error—often discussed in relation to 'unreliability' (see Bliese, 2000). Further, the problems caused by such bias are exacerbated when squaring variables or forming interaction terms as in Equation 1 (see Moosbrugger, Schermelleh-Engel, Kelava, & Klein, 2009). In order to eliminate the biasing effects of sampling error requires a latent variable approach with random effects, variously referred to as 'multilevel modeling' or 'hierarchical linear modeling'. In such an approach, latent 'random intercepts' are estimated to represent the standing of higher-level entities along outcomes such as *QI* that are measured at a lower level of analysis.

Although the traditional multilevel modeling approach with random intercepts is meant to separate the between- and within-cluster variation in an outcomes variable, the raison d'être of random intercepts in such models is to correct for sampling error by using a combination of approaches called 'precision-weighting' and 'empirical Bayes' or 'shrinkage' estimation. These procedures adjust estimates of grand-means and cluster means based on estimates of uncertainty in the form of sampling error variance (see Raudenbush & Bryk, 2002). In brief, as the sample size within a cluster decreases and as a variable's variance within a cluster increases, larger adjustments are made because smaller sample sizes and larger variances equate to larger amounts of sampling error. The result is estimates of grand means and higher-level standings along outcome variables that are corrected for sampling error. However, as useful as this approach is, it does not model random intercepts for predictors and therefore cannot estimate latent interactions among these intercepts in order to create the squared and product terms required in Equation 1.

To overcome these difficulties we develop the MLPM as a special case of the multilevel structural equation modeling (MSEM) framework described in Muthén and Asparouhov (2008) and Preacher, Zyphur, and Zhang (2010). The logic of SEM is the same as traditional multilevel models except the decomposition of within- and between-cluster variance as well as precision-weighting and empirical Bayes estimation are done for all variables, including predictors (see Lüdtke et al., 2008). In brief, MSEM can be thought of as extending the logic of random intercepts to all variables in a model (not only a predictor) with the benefits of structural equation models, including complex measurement and structural relationships, and latent interactions.

Consistent with such capabilities, MSEM allows estimating all variables in Equation 1 as random intercepts (i.e., CC_M, CC_{NM}, and QI) or as latent interactions (i.e., squared and product terms). It is this model that we refer to as an MLPM. Although it is not our focus here, because the MLPM is a special case of MSEM, it can be extended to correct for measurement error by estimating latent factors that are reflected by multiple observed variables (see Marsh et al., 2009). Also, it is notable that the logic of latent interactions in the MLPM can be extended to estimate multilevel moderation/interactions among predictors at within- or between-cluster levels (as in Preacher, Zhang, & Zyphur, in press)—we treat MLPM extensions in our discussion.

The MLPM as applied here treats an individual *i* as nested in an organization *j* along QI_{ij}, CC_{Mij}, and CC_{NMij}. Data are arbitrarily ordered within each organization along these variables, reflecting the irrelevance of the within-organization part of the model (each sampled individual is either a manager or a non-manager and therefore only has a score on either CC_{Mij} or CC_{NMij}, so these variables have no meaningful within-organization covariance; see Appendix A with an example dataset for the MLPM). The number of QI observations for each organization is equal to its number of managers and non-managers, while CC_M will have observations equal to the number of managers, and CC_{NM} will have observations equal to the number of non-managers. In turn, CC_M and CC_{NM} will always have empty cells within each organization because *QI* will always contain more data than each predictor—if *QI* were measured at the organization level, this would not be true. Specifically, CC_M will have a number of empty cells equal to the number of non-managers, and CC_{NM} will have a number of empty cells equal to the number of managers (see Appendix A). All empty cells should be treated as missing data, which allows parameter estimation of organization standings along each variable when using full-information estimators (the default in programs such as Mplus. In turn, this ordering of the data causes all within-organization covariance to be arbitrary, but this is irrelevant because the focus of the MLPM is only on between-organization (i.e., organization level) model elements that we now describe.

In brief, the MLPM allows estimating latent organization standings along three variables, one of which is an organizational outcome such as *QI*, with the other two variables representing the standings of two organizational groups along a predictor such as CC_M and CC_{NM}. The MLPM decomposes within- and between-organization parts of these variables as follows:

$$\mathbf{Y}_{ij} = \boldsymbol{\Lambda\eta}_{ij} \tag{2}$$

and

$$\boldsymbol{\eta}_{ij} = \boldsymbol{\alpha}_j + \boldsymbol{\zeta}_{ij}; \tag{3}$$

wherein $\mathbf{Y}_{ij}$ is a *p*-dimensional vector of observed variables for person *i* in organization *j*, $\boldsymbol{\Lambda}$ is a *p* x *m* matrix of ‘loadings’ that link individuals to organizations, $\boldsymbol{\eta}_{ij}$ is a *m*-dimensional vector of within- and between-organization parts of observed variables, $\boldsymbol{\alpha}_j$ is a *m*-dimensional vector of intercepts allowed to randomly vary across organizations to capture between-organization variation, and ζ_{ij} is a *m*-dimensional vector of disturbances that capture within-organization variation. The relevant between-organization model can be shown as follows:

$$\eta_j = \mu + B\eta_j + \zeta_j; \qquad (4)$$

wherein η_j is an *r*-dimensional vector that stacks random intercepts and for the sake of simplicity here includes latent product terms as variables (notice that η_j is different from η_{ij}), μ is an *r*-dimensional vector of fixed intercepts, $\mathbf{B}$ is an *r* x *r* matrix of fixed effects, and ζ_j is an *r*-dimensional vector of disturbances. Of note is that adjustments for sampling error associated with elements in α_j are also applied to elements in μ, so that both are adjusted for sampling error (for detailed treatment see Raudenbush & Bryk, 2002). In turn, hypotheses related to grand-mean differences such as Hypothesis 2 can be tested with corrections for sampling error by testing for differences in elements of μ that correspond to the predictors (i.e., CC_M and CC_{NM}). Of note is that such tests are neither between-cluster nor within-cluster tests and, instead, are tests of differences in grand-means for organizational groups across all clusters (i.e., culture perceptions for all managers compared to culture perceptions for all managers across all organizations).

For our MLPM, the matrices and vectors contain elements as follows (we include an observed organization-level variable *Size* that is described as a control variable in our Method section, in part to illustrate how the MLPM, just like MSEM, can accommodate predictors or outcomes measured at the cluster level [e.g., *QI* could have been so measured and the MLPM would still be useful for treating the predictors CC_M and CC_{NM} as latent random intercepts]):

$$\mathbf{Y}_{ij} = \begin{bmatrix} QI_{ij} \\ CC_{Mij} \\ CC_{NMij} \\ Size_j \end{bmatrix} = \Lambda\boldsymbol{\eta}_{ij} = \left[\begin{array}{ccc:cccc} 1 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{array}\right] \left[\begin{array}{c} \eta_{QI_{ij}} \\ \eta_{CC_{Mij}} \\ \eta_{CC_{NMij}} \\ \hdashline \eta_{QI_j} \\ \eta_{CC_{Mj}} \\ \eta_{CC_{NMj}} \\ \eta_{Size_j} \end{array}\right] \tag{5}$$

and

$$\boldsymbol{\eta}_{ij} = \left[\begin{array}{c} \eta_{QI_{ij}} \\ \eta_{CC_{Mij}} \\ \eta_{CC_{NMij}} \\ \hdashline \eta_{QI_j} \\ \eta_{CC_{Mj}} \\ \eta_{CC_{NMj}} \\ \eta_{Size_j} \end{array}\right] = \boldsymbol{\alpha}_j + \boldsymbol{\zeta}_{ij} = \left[\begin{array}{c} 0 \\ 0 \\ 0 \\ \hdashline \alpha_{QI_j} \\ \alpha_{CC_{Mj}} \\ \alpha_{CC_{NMj}} \\ \alpha_{Size_j} \end{array}\right] + \left[\begin{array}{c} \zeta_{QI_{ij}} \\ \zeta_{CC_{Mij}} \\ \zeta_{CC_{NMij}} \\ \hdashline 0 \\ 0 \\ 0 \\ 0 \end{array}\right] \tag{6}$$

Here, within- and between-organization terms are partitioned with dashed lines, showing how the vector $\boldsymbol{\zeta}_{ij}$ captures irrelevant within-organization terms while the vector $\boldsymbol{\alpha}_j$ contains the latent between-organization random intercepts of interest.

The relevant between-organization model that mimics Equation 1 can be shown as

$$\boldsymbol{\eta}_j = \begin{bmatrix} \alpha_{QI_j} \\ \alpha_{CC_{Mj}} \\ \alpha_{CC_{NMj}} \\ \alpha^2_{CC_{Mj}} \\ \alpha_{CC_{Mj}*CC_{NMj}} \\ \alpha^2_{CC_{NMj}} \\ \alpha_{Size_j} \end{bmatrix} = \boldsymbol{\mu} + \mathbf{B}\boldsymbol{\eta}_j + \boldsymbol{\zeta}_j =$$

$$\begin{bmatrix} \mu_{QI} \\ \mu_{CC_M} \\ \mu_{CC_{NM}} \\ 0 \\ 0 \\ 0 \\ \mu_{Size} \end{bmatrix} + \begin{bmatrix} 0 & \beta_{12} & \beta_{13} & \beta_{14} & \beta_{15} & \beta_{16} & \beta_{17} \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} \alpha_{QI_j} \\ \alpha_{CC_{Mj}} \\ \alpha_{CC_{NMj}} \\ \alpha^2_{CC_{Mj}} \\ \alpha_{CC_{Mj}*CC_{NMj}} \\ \alpha^2_{CC_{NMj}} \\ \alpha_{Size_j} \end{bmatrix} + \begin{bmatrix} \zeta_{QI_j} \\ \zeta_{CC_{Mj}} \\ \zeta_{CC_{NMj}} \\ 0 \\ 0 \\ 0 \\ \zeta_{Size_j} \end{bmatrix} \qquad (7)$$

wherein the latent between-organization random intercept of *QI* (a_{QI_j}) is a function of the control variable *Size* as well as the latent between-organization random intercepts of both *CC* variables ($a_{CC_{Mj}}$ and $a_{CC_{NMj}}$), the square of these variables ($a^2_{CC_{Mj}}$ and $a^2_{CC_{NMj}}$), as well as their product ($a_{CC_{Mj}*CC_{NMj}}$). To aid in the interpretation of Equation 7, the terms in $\boldsymbol{\eta}_j$ are ordered so that they can be related to those in Equation 1, wherein the βs have subscripts that link Equations 7 and 1 as follows: $b_{12} \Leftrightarrow b_2$, $b_{13} \Leftrightarrow b_3$, …, $b_{16} \Leftrightarrow b_6$.

Although estimating the random intercepts a_{QI_j}, $a_{CC_{Mj}}$, and $a_{CC_{NMj}}$ is straightforward in MSEM (see Lüdtke et al., 2008), this is not true for the latent squared and product terms $a^2_{CC_{Mj}}$, $a^2_{CC_{NMj}}$, and $a_{CC_{Mj}*CC_{NMj}}$, which require a method for multiplying latent variables by themselves and each other. For this we use the latent moderated structural equations (LMS) approach of

Klein and Moosbrugger (2000), as implemented in Mplus (see program code in Appendix B). This approach allows estimating $a^2_{CC_{Mj}}$, $a^2_{CC_{NMj}}$, and $a_{CC_{Mj}*CC_{NMj}}$ as latent interactions that are treated as random slopes (see Muthén & Asparouhov, 2003). A similar approach has been used for single-level models that mimic Equation 1 with latent variables (e.g., Klein, Schermelleh-Engel, Moosbrugger, & Kelava, 2009; Moosbrugger et al., 2009) and within-cluster models that are roughly equivalent (see Marsh et al., 2009), but we are aware of no previous work that extends this to the multilevel case with random intercepts as in Equation 7.

Before implementing the MLPM by estimating the relevant response surface parameters and testing our hypotheses, there are three important points to make. First, LMS assumes normality of latent variables involved in interactions (Klein & Moosbrugger, 2000). Fortunately, normality can be expected to hold for random intercepts under assumptions related to the central limit theorem. Second, there are alternatives to LMS for estimating latent interactions, but LMS compares favorably to these across a variety of circumstances (Klein et al., 2009).

Third, the raison d'être of the MLPM is to estimate the β terms in Equation 7 so that these can be used to create compound statistics that describe the response surface for *QI*, CC_M, and CC_{NM} (see Edwards & Parry, 1993; Edwards, 1994; for insight see also the MODEL CONSTRAINT portion of Appendix B, but note that results from this part of the model should only be used to understand the statistics involved rather than for hypothesis testing). However, many of these compound statistics do not have a known sampling distribution, so most authors use non-parametric bootstrapping to create confidence intervals (CI) to test hypotheses (e.g., Edwards & Cable, 2009). Unfortunately, with multilevel data there is no one way to do this because of the clustered sampling (see Field & Welsh, 2007). Instead, to estimate CIs with multilevel data researchers can use a Monte Carlo method, parametric bootstrapping, or Bayesian posteriors (Preacher et al., 2010). A Bayesian approach is ruled out because the current version of Mplus does not allow it for latent interactions, and parametric bootstrapping is computationally difficult with latent interactions that require high-dimensional numerical integration. Therefore, for MLPMs we propose a Monte Carlo method that compares favorably with other approaches (for a more detailed discussion see Beisanz, Falk, & Savalei, 2010; Preacher & Selig, 2012).

A Monte Carlo approach to response surface CIs requires treating Equation 7 parameters (i.e., $\beta_{12} + \beta_{13}$, etc.) as random variables to simulate estimates of each parameter (see Mplus program code in Appendix C). To do this, observed data allow estimating MLPM parameters and their asymptotic covariances. These are then used to parameterize random variables for a Monte Carlo simulation. Next, 10,000 estimates for each parameter are generated and then used to compute 10,000 response surfaces. CIs can then be constructed by examining the bottom 2.5% and the top 97.5% for each response surface parameter of interest—these parameters are later described as they relate to our Hypotheses (see also Edwards, 1994; Edwards & Parry, 1993; see also the MODEL CONSTRAINT portion of Appendix B).

Method

We reanalyze data from Shortell et al.'s (1995) study using the variables they developed. They examined the implementation of continuous quality improvement/total quality management (CQI/TQM) practices in 67 U.S. hospitals. The survey included items profiling cultural content as the CVF and the sample contained, on average, 100 managerial and non-managerial respondents in each hospital. We begin by describing Shortell et al.'s study.

Study Background and Sample

Health care reforms in the 1980s increased pressures on U.S. hospitals to improve the quality of care and contain costs. As a result, hospitals experimented with CQI/TQM programs being implemented in U.S. industry (Westphal, Gulati, & Shortell, 1997) and, by 1993, 69% of U.S. hospitals had formal, full-scale CQI/TQM programs in place (Barness et al., 1993). During this period of rapid uptake, Shortell et al. (1995) collected data in 67 hospitals that were comparable to the population of U.S. hospitals with regard to bed size and occupancy.[1] A questionnaire was administered to senior and middle managers, and clinical and administrative non-managers. Up to 200 people were sampled per hospital with a response rate of 72% (N = 7,337), ranging from 56% to 100%. After eliminating questionnaires with missing data as in Shortell et al. (1995), our analysis is based on a sample of 6,731 respondents, including 281 (4%) senior managers, 1,058 (16%) middle managers, and 5,392 (80%) clinical and administrative non-managers. We classified senior and middle managers as "managers" for our analysis.

Measures

Quality improvement implementation. We measured management innovation with a 38-item scale developed by Shortell et al. (1995) to assess the degree of quality improvement practice implementation, which we continue to refer to as *QI*. This measure is based on Malcolm Baldrige National Quality Award criteria—common in CQI/TQM research (Prajogo & McDermott, 2005). The scale has six subscales: leadership (10 items, $\alpha = 0.93$), information and analysis (7 items, $\alpha = 0.86$), human resources utilization-empowerment (5 items, $\alpha = 0.80$), human resources utilization-training and development (3 items, $\alpha = 0.79$), quality management (6

[1] Shortell et al. (1995) reports results based on 61 of the 67 hospitals in our sample. Their data were from several sources and they excluded hospitals with missing data. Our study uses data primarily from one survey of Shortell et al.'s study, with complete data for the QI and culture variables available for all 67 hospitals. Information for the number of beds control variable was not available for two hospitals. Because this variable was not significant in Shortell et al.'s study, we preserved sample size by using average bed size to replace the two missing values.

items, $\alpha = 0.88$) and strategic quality planning (7 items, $\alpha = 0.85$). Items focused on quality improvement behaviors such as: (1) "Hospital employees are actively involved in determining what data are collected for the purpose of improving the quality of services" (information and analysis) and (2) "Hospital employees are given education and training in how to identify and solve quality problems" (human resource utilization-training and development). The survey instrument used a five point Likert-type scale ranging from 1 (strongly disagree) to 5 (strongly agree). Higher scores indicate greater *QI*. For additional information, see Shortell et al. (1995).

The scales were highly correlated (average $r = 0.76$), so Shortell et al. (1995) calculated an overall *QI* score by averaging the six subscales across managers and non-managers. The difference between manager and non-manager ratings were not statistically significant ($\Delta = 0.03$, $t = 1.24$, $p = 0.22$, $\eta^2 < 0.001$). We follow Shortell et al. and use managers and non-managers to measure a hospital's *QI* (as implied by the MLPM presented earlier).

Because the MLPM models between-hospital effects, we computed the reliability of *QI* scores at the hospital level with a multilevel model wherein variances and covariances for all 38 items were estimated. Using these estimates, we computed α as described in Geldhof, Preacher, and Zyphur (2014), which was .99. The ICC(1) for this variable is 0.08 (equivalent to the performance variable in Gibson et al., 2009) and was estimated as a proportion of latent variance in our MLPM (described below). Although researchers are often concerned about 'reliability' as ICC(2) in the multilevel context (see Bliese, 2000), in the MLPM there is no interpretable ICC(2) because hospital standings are treated as latent rather than using means and, therefore, our parameter estimates are corrected for sampling error that causes unreliability as 1 – ICC(2).

Cultural content. This was assessed with a five-item scale based on the CVF, using Shortell et al.'s (1995) version of Zammuto and Krakower's (1991) measure. Each item required dividing 100 points among four scenarios based on the similarity of one's hospital to a scenario, each of which fit into a quadrant. Thus, a score for each quadrant is the average of the number out of 100 given to the quadrant for each of the five items (e.g., scores of 10, 15, 20, 25, and 30 for the human relations quadrant for the five items would net a human relations score of 20).

Shortell et al. (1995) dealt with the potential problems due to the ipsative data by creating a 'flexibility' variable that sums the human relations and open systems quadrants to focus on the preference for structuring axis of the CVF, wherein higher scores show more flexible structuring by internalizing coordination and control. Lower scores indicate greater reliance on formal bureaucratic mechanisms, such as formal rules and policies. To mimic Shortell et al.'s approach, we did the same. As above, we calculated coefficient alpha for the flexibility variable at the hospital level, which was 0.79. The model-estimated ICC(1) was 0.15, which is comparable to that reported in three multi-respondent studies in Hartnell et al.'s (2011) meta-analysis (see Aarons & Sawitzky, 2006; Erdogan, Liden, & Kraimer, 2006; Glisson & James, 2002). No interpretable ICC(2) exists because the MLPM corrects for sampling error in its estimates.

To facilitate interpretation of the estimated regression coefficients, the manager and non-manager cultural content variables were centered around the scale midpoint of 50 (see Edwards, 1994). To ease model estimation, both cultural content variables were divided by 10.

Hospital size. To adjust for the effects of organization size, we controlled for the number of beds in a hospital as Shortell et al. did (1995). They also included a CQI/TQM dummy variable to indicate whether a hospital had formally adopted a formal CQI/TQM program, which was not related to *QI* in their analysis. As it was not available in the dataset we obtained, it is not included here. We grand-mean centered the *Size* variable and divided it by 100 to increase the interpretability of parameter estimates and ease model estimation, respectively.

Results

We specified a MLPM in Mplus 7 (Muthén & Muthén, 1998-2012) with a maximum likelihood estimator robust to non-normality (see program code in Appendix B). Table 1 reports descriptive statistics and Table 2 reports the multilevel latent polynomial model results—descriptive statistics do not reflect response surfaces, so we do not discuss them. To justify our higher-order terms we estimated an MLPM in a series of steps, computing a pseudo-R^2 at each step (Raudenbush & Bryk, 2002). We first estimated a model with *QI* as a latent variable at the hospital level, with an estimated variance of .34. We then added the control variable to account for hospital size, which reduced the variance to .32 (pseudo-R^2 = .06). We then added the manager and non-manager cultural content predictor variables, which reduced the variance to.13 (pseudo-R^2 = 0.62, Δpseudo-R^2 = 0.56). We added the polynomial and interaction terms as predictors (see Figure 1), which reduced the variance to a degree that caused Mplus to fix the variance to zero in order to assist convergence. We take these results to indicate that not only are manager and non-manager cultural content perceptions important for *QI*, but the non-linear joint relationship between these perceptions is important to consider. In other words, the congruence of managers and non-managers cultural perceptions is an important predictor of *QI*, which motivates examining the response surface among the variables.

Insert Tables 1 and 2 and Figure 1 about here

Response Surface Analysis

Hypothesis 1 states that higher manager and non-manager cultural content scores indicating a greater emphasis on humanistic and innovative values will be positively related to

QI. This hypothesis was tested by examining the slope that defines the response surface along the line of congruence between manager and non-manager cultural content perceptions (see the solid line along the *x*, *z* plane in Figure 2). The positive slope indicates that as both manager and non-manager perceptions of humanistic and innovative values increase, *QI* increases, supporting Hypothesis 1. Shown in Table 2, the slope of the response surface along the line of congruence was positive ($a_1 = \beta_{12} + \beta_{13} = 0.24$) and the 95% CI did not include zero (ranging 0.02 to 0.45). Also, this slope appears linear, with a negative curve estimated almost exactly at zero ($a_2 = \beta_{14} + \beta_{15} + \beta_{16} = -0.01$) and a 95% CI centered nearly at zero (ranging -0.17 to 0.14).

Insert Figure 2 about here

Hypothesis 2 states that managers will perceive cultural content as more humanistic and innovative than non-managers. This was tested as the difference between means for latent manager and non-manager culture variables. This difference was positive (m_{C_M} - $m_{C_{MN}}$ = Δ = 1.05) and statistically significant ($t = 18.15$, $p < 0.01$), showing that managers systematically perceive the content of their organization's cultures as being more humanistic and innovative and less controlling and task-focused compared to non-managers. This supports Hypothesis 2.

Hypothesis 3 proposes that incongruence between manager and non-manager perceptions of cultural content negatively impacts *QI*. This hypothesis was tested by examining the curve that defines the response surface on the line of incongruence between manager and non-manager culture perceptions (see the dashed line along the *x*, *z* plane in Figure 2). A negative curve shows that as manager and non-manager perceptions become more incongruent, *QI* decreases. The curve of the surface along the line of incongruence was negative ($a_3 = \beta_{14} – \beta_{15} + \beta_{16} = -1.76$) and the 95% CI did not include zero (ranging -2.89 to -0.68), supporting Hypothesis 3.

We further examined the negative curve along the line of incongruence with two tests involving the first principle axis of the response surface (see Edwards & Cable 2009). This axis describes where the response surface peaks. If incongruence reduces *QI* across the full range of manager and non-manager cultural content, this axis should be parallel to the line of congruence (a slope of 1.0) and run along the line of congruence (an intercept of 0). Such a finding indicates that moving away from perfect congruence is uniformly negative for *QI*. We find that the slope of the axis is almost exactly 1.0 (p_{11} = 1.07), and the 95% CI is centered near 1.0 (ranging 0.31 to 1.51). We find that the axis intercept differed slightly from 0.0 (p_{10} = -0.51), but the 95% CI was centered near zero (ranging -5.38 to 5.1). In addition to the above findings, these properties of the response surface support Hypothesis 3 by showing that deviation from perfect congruence between managers and non-managers reduces *QI* across the full range of cultural content scores.

To gain a better understanding of the differences between manager and non-managers, we conducted a post hoc analysis of CVF scores, comparing hospitals that were less versus more congruent. We first calculated the degree of congruence in each hospital by summing the difference between manager and non-manager mean scores for each CVF quadrant. Absolute values of the differences were used because of the ipsative nature of the quadrant scores (e.g., simply summing the differences across the quadrants would have resulted in an overall score of zero). Higher scores indicate greater differences in perceptions between managers and non-managers. Second, we split the sample into more congruent (congruent subsample) and less congruent (incongruent subsample) subsamples using the median congruence score.

We then compared the CVF quadrant scores' mean differences within and across the subsamples. Comparing manager and non-manager perceptions in the congruent subsample (Table 3a) shows that manager and non-manager quadrant scores are highly correlated, ranging from $r = 0.81$ to 0.89 ($p < 0.01$). However, managers' human relations scores were statistically significantly higher than non-managers' scores by three points ($t = 3.50$, $p < 0.01$), and non-managers' internal process scores were higher than managers' scores by four points (of the total 100 points distributed across the four quadrants; $t = 5.86$, $p < 0.01$). The differences for the open systems and rational goal scores were smaller and not statistically significant.

Insert Table 3 about here

Comparing manager and non-manager perceptions in the incongruent subsample shows a different picture (see Table 3b). Correlations among manager and non-manager quadrant scores decreased considerably, ranging from $r = 0.30$ (*n.s.*) to 0.64 ($p < 0.01$), and mean differences were significant for all quadrants (t ranged from 2.04 to 12.41, $p < 0.05$). Managers perceived cultural content as being significantly more humanistic and innovative, and less controlling and task oriented, than non-managers. The size of the differences is also larger than in the congruent subsample. The difference in human relations scores increases to 10 points, and to 11 points for internal process, which is roughly three times that observed in the more congruent subsample.

Comparing manager scores across the two subsamples shows that their perceptions of cultural content are virtually identical. That is, managers assessed the cultural content in their hospitals similarly regardless of whether the differences in their perceptions with non-managers in their hospitals were more or less congruent. In contrast, non-managers' perceptions of cultural content were significantly different across the subsamples. Non-managers in the incongruent subsample perceived the cultural content of their hospitals as being significantly less humanistic (lower human relations score) and more controlling (higher internal process and rational goal scores) than non-managers in the congruent subsample ($p < 0.05$). Overall, the post-hoc analysis provides additional support for Hypotheses 2 and 3, illustrating how incongruent perceptions of cultural content in these hospitals manifested in terms of the CVF raw scores.

Discussion

A substantial amount of organizational research purports to represent phenomena and entities such as individuals, groups, and organizations across a wide range of characteristics. However, various areas of research only sometimes take seriously the importance of representing the multiple organizational groups that define organizations. In these and other cases, questions arise regarding the existence and effects of (in)congruence across organizational groups. To test such hypotheses, we develop and deploy a novel MLPM, applying it to the case of organizational culture research to show that sampling managers alone not only misrepresents organizational culture on average, but also that management innovation in the form of quality implementation is reduced as congruence between managers and non-managers decreases. Other research areas, such as that on high-performance work systems, organizational strategy, and leader-member exchange may be characterized by similar effects. In what follows we first discuss our novel MLPM and then we explore the implications of our organizational culture findings.

The MLPM and General Latent Variable Modeling

Organization researchers often desire to advance organization science by overcoming methodological limitations. In order to understand and overcome such limitations, it is important to recognize that many of them occur because of the way existing methods are talked about and materialized in, for example, statistics software. A relevant example is the way that researchers understand multilevel modeling as described in, for example, Raudenbush and Bryk (2002), which is instantiated in research practices through the program HLM. Because this approach historically limited random intercepts to outcome variables and these outcome variables needed to be measured at the lowest level of analysis, some researchers may have erroneously come to believe that ‘multilevel modeling’ necessarily has these features/limitations.

However, when examining Raudenbush and Bryk (2002), the core of their approach that goes beyond single-level regression involves attending to different sources of variation (e.g., within- versus between-cluster), along with precision-weighting and empirical Bayes or shrinkage estimates of higher-level parameters. When these are understood as being at the heart of multilevel modeling, the traditional HLM model becomes merely a special case in a more general MSEM framework that is vastly more capable (see Muthén & Asparouhov, 2008; Preacher et al., 2010; Preacher et al., in press). In turn, the limitations of ‘multilevel models’ end up partly being about the way these models are often understood in terms of HLM, and therefore such limitations have the potential to evaporate when researchers free themselves to use frameworks that are more general, such as MSEM (see Marsh et al., 2009). The point is that overcoming some limitations may merely require reconceptualizing a method and its purposes in order to figure out creative solutions to existing problems (i.e., a new narrative about what researchers and methods are doing).

As a case in point, the MLPM is a special case in a more general MSEM framework. The innovation of the MLPM is not necessarily in treating predictors as latent variables at higher levels of analysis—many papers on MSEM describe this (e.g., Preacher et al., 2010). Instead, the innovation is in understanding how the potential for latent interactions as developed for single-level structural equation models can be applied to random intercepts in multilevel models. In part, it is because these variables are called ‘random intercepts’ and often understood in relation to ‘multilevel modeling’ that researchers may heretofore have not considered involving them in latent interactions that were developed for and spoken about in relation to ‘structural equation models' with latent variables as 'factors'. Thus, the MLPM has been possible for some time, and its development merely required rethinking latent interactions and their uses in MSEM. Similarly, other novel models are possible as special cases in a general MSEM framework as implemented in programs like Mplus, and future research can be pointed at such developments.

For example, future work can generalize our approach and that taken by Marsh and colleagues with latent interactions in MSEM at the within-group level of analysis (for details see Preacher et al., in press). Such future work might describe an even more general latent variable framework allowing latent interactions with the LMS approach as well as with more traditional random slopes—these necessarily involve latent interactions whenever predictors with random slopes are latent variables. In turn, approaches to multilevel moderation may be revolutionized by allowing latent interactions among the within- and/or between-group parts of variables measured at the individual level, which heretofore has been missing from all discussions with which we are familiar. Indeed, existing multilevel moderation approaches calculate means rather than using random intercepts (e.g., Aguinis, Gottfredson, & Culpepper, 2013; Cronbach & Webb, 1975; Enders & Tofighi, 2007; Hofmann & Gavin, 1998; Mathieu, Aguinis, Culpepper, & Chen, 2012; Raudenbush, 1989a, 1989b; Raudenbush & Bryk, 1986), but this biases parameter estimates in the presence of sampling error (Preacher et al., 2010). Future work may overcome this bias by taking an approach to latent interactions as we describe here, as well as overcoming bias caused by including measurement models at multiple levels (as in Marsh et al., 2009).

This said, it is notable that our MLPM approach and the use of random intercepts for outcomes or predictors more generally should not be considered unilaterally better than other approaches, such as using calculated means instead of random intercepts. The point of estimating a random intercept as a latent variable is to correct for sampling error, and such a correction in cases wherein all members of a group or organization have been sampled may not be appropriate (Lüdtke et al., 2008; Marsh et al., 2009). Corrections for sampling error are predicated on the notion that individuals have been incompletely sampled within a group or organization, just as corrections for measurement error can be predicated on the classical-test-theory idea that items have been incompletely sampled to reflect standings along attributes of interest. When this assumption does not hold—when individuals cannot be understood as imperfectly 'reflecting' the standing of higher-level units—then researchers may calculate means instead of resorting to more complex approaches such as the MLPM described here.

Indeed, by using means instead of random intercepts, researchers overcome two issues that trouble the MLPM and other models that involve latent interactions: computation time and convergence. Currently, programs like Mplus only implement an LMS approach with maximum-likelihood estimation. The result is that numerical integration is required for estimating latent interactions. As the number of latent variables in a model increases, the dimensions of this integration also increase, which can rapidly cause estimation times to become unreasonable and can also cause convergence problems—it is for these reasons that we calculated means across the scale items for our variables rather than specifying a measurement model and computing latent interactions among latent factors. For now, there is no easy solution to these problems, but future advances in computing power and extensions to a Bayes estimator should ease both difficulties.

Another important issue for multilevel modeling and polynomial regression analysis is the issue of centering Level-1 variables. In single-level polynomial regressions, the two predictors can be centered around the common scale mid-point, around their pooled grand mean (with our data this would be the mean of all managers' and non-managers' cultural content), or around the respective means of each predictor (i.e., centering CC_M around its mean, and centering CC_{NM} around its mean). Edwards (1994) recommended centering around scale mid-points to facilitate interpretation (which we did in the current study). In contrast, in multilevel research, centering methods on Level-1 variables have critical implications that go beyond the discussion in Edwards (1994). Unlike the SEM approach we adopt here that automatically separates within- and between-group variation, in HLM-styled multilevel modeling grand-mean centering or using raw scores (no centering) necessarily conflates within- and between-group effects when these differ (Preacher et al., 2010, Raudenbush, 1989a). Therefore, group-mean centering is recommended when researchers examine within-level or cross-level relationships (Enders & Tofighi, 2007; Hofmann & Gavin, 1998).

Combining multilevel modeling and polynomial regressions makes the centering decisions more complex. In the current study, we used scale mid-point centering which is analytically equivalent to grand-mean centering in an MLM sense (because a scalar was deducted from the two predictors). This centering approach typically would create conflation issues if we were to focus on within, within + between, or cross-level effects. Fortunately, because our theory and analysis focus on between-level effects, we were able to avoid such conflation issues while keeping our centering method aligned with conventional polynomial regression practices. However, when researchers extend the MLPM to examine congruence at the within level, we recommend they use group-mean centering to minimize potential conflations, which is automatically done in the MSEM framework as implemented in Mplus. Using our recommended data structure (wherein managers have empty cells along non-manager perceptions, and vice versa), for the within part of any MSEM in Mplus, manager and non-manager variables will be centered around their respective organization means.

Organizational Culture Research and Findings

The value of the MLPM can be seen as we discuss how our findings lead to a more nuanced understanding of the relationship between organizational culture and management innovation, and the implications of our results for organizational culture research more generally. Consistent with prior research, we confirm that a culture's content—its underlying values, assumptions, and beliefs—is related to management innovation in the form of quality implementation. Cultural content emphasizing the CVF's human relations and open systems quadrants had a positive relationship with *QI* in the hospitals surveyed. This finding is broadly indicative of the survey-based research that focuses on the relationship between cultural content and various dimensions of organizational performance such as management innovation. The greater the emphasis on humanistic and innovative values, the higher the level of performance.

Unlike prior research, we examined the extent to which values were shared by managers and non-managers in an organization and whether differences in their cultural perceptions were related to management innovation. We found that managers, on average, perceived their cultural values and beliefs as significantly more humanistic and innovative, and less controlling and task-focused than non-managers. We also found that the magnitude of these differences was negatively related to management innovation and explained about half again as much variation in *QI* as did cultural content alone. Lower congruence between manager and non-manager perceptions was associated with lower *QI* across the full range of cultural content scores. Literally interpreted, the extent to which manager and non-manager cultural realities were different had an independent, negative relationship with *QI*. These findings raise questions about the validity of results reported by past research on the culture-innovation relationship and about the culture-performance relationship more generally.

Specifically, studies using manager-only samples (70% of studies in Hartnell et al.'s 2011 meta-analysis) have potential validity problems because non-managers' perceptions of cultural content have not been assessed and therefore the extent to which cultural congruence exists cannot be determined nor its effects examined. Our analysis of the CVF scores for the congruent subsample showed that manager and non-manager ratings of cultural content are highly correlated when perceptions are congruent, meaning that validity is not an issue when there is a high level of congruence. However, our analysis of the incongruent subsample showed that correlations between manager and non-manager ratings of the CVF's quadrants decreased as incongruence increased, meaning that validity *is* an issue when manager and non-manager perceptions of cultural content are incongruent. As correlations between managers and non-managers decrease, the relationships between manager-rated culture and any other variables will not show the same pattern as non-manager-rated culture and those same variables. The implication is that as cultural congruence decreases, manager ratings of cultural content become invalid proxies for non-managers ratings and vice versa. Our findings show that, on average, managers and non-managers are different, so it is reasonable to expect that in many cases managers and non-managers ratings are not exchangeable.

This argument contradicts received wisdom on sampling in survey-based organizational culture-performance studies in Hartnell et al.'s (2011) meta-analysis (i.e., the bulk of published quantitative studies), where some researchers attempt to justify single-respondent and manager-only samples. Although these studies define organizational culture as a 'shared' phenomenon, researchers have argued that manager-only and single-respondent samples are justified because: culture at the highest levels of the organization may be most directly linked to performance; that previous studies indicate that top managers are a reliable source of information; that a key informant approach is being used; or that it is justified because other researchers have done it.

These justifications do not reflect the findings from our study, nor do they take seriously the moral position of valuing the realities of managers over non-managers, the latter of whom systematically report less desirable cultural content as our findings for Hypothesis 2 show. Our results call into question the ability to generalize and meta-analytically synthesize the findings from studies of organizational culture that treat managers and non-managers as exchangeable without examining the congruence of their ratings. The results indicate that examinations of congruence should be done, and only when managers and non-managers perceptions are congruent should generalizations and meta-analysis be conducted across manager and non-manager populations. Unfortunately, because non-managers perceptions of cultural content are not assessed in most published work, the extent to which congruence exists cannot be determined, raising concerns about the validity of results from manager-only studies.

This same logic also applies to most of the remaining studies on organizational culture, and specifically those studies that sample both managers and non-managers and aggregate their cultural content measure into organization-level means (15% of the Hartnell et al.'s 2011 studies). Unfortunately, these studies can also suffer from validity problems even though manager and non-manager ratings of cultural content are obtained. As with manager-only samples, when manager and non-manager ratings are congruent then validity is not an issue—as our post hoc analyses show. But as congruence decreases, calculating an organization-level mean can mask these differences and ignore the different correlations across the groups in terms of culture perceptions and *QI*, making the mean an invalid proxy for *both* managers' and non-managers' ratings of cultural content *and* its relationship with other variables.

At a minimum, researchers using samples of managers and non-managers should assess the extent that congruence exists between manager and non-manager ratings of cultural content. Indeed, our results show that even small differences in congruence appear to moderate the relationship among cultural content and management innovation. We suggest that researchers with samples including managers and non-managers consider the analytical technique presented in our study—response surface modeling with MLPM—as an alternative approach that would allow them to examine the joint effects of cultural content and congruence.

Conclusion

We think it likely that (in)congruence may affect other organizational phenomena that involve members of two or more groups within an organization and where samples are intended to be representative. Our results suggest that assuming representativeness or congruence in perceptions across groups may lead to a flawed sampling strategy that invalidates results. It also suggests that the single-respondent sampling in much organizational research may be problematic, such as in studies of high-performance work systems, strategy implementation, and leader-member exchange. Future research should not only attempt to understand the implications and applications of our results for organizational culture, but also how our findings and the MLPM can inform non-representative research that is common in other areas of study. If we, as researchers, define constructs as being about what is shared across people or what is occurring in an organization, then we need to assess the extent to which our research discourse matches our research practice, or at a minimum be honest about whose views are being represented in our studies. To the extent that our studies have tended to favor the views of managers instead of non-managers, it seems time to redress this shortcoming and start looking at the realities that exist beyond the managerial purview.

Appendix A

To arrange data for an MLPM, start with 'long' format data for two organizational groups along two variables, here culture perceptions (*CC*) and quality implementation (*QI*) for managers (*M*) and non-managers (*NM*), with organization membership coded in a variable '*Org*' and group membership coded in a variable '*Org Group*' as follows:

CC	*QI*	*Org*	*Org Group*
2	5	1	M
4	2	1	M
6	4	1	NM
8	5	1	NM
9	7	1	NM
1	1	2	M
2	2	2	M
4	3	2	NM
6	5	2	NM.

Rearrange the data so that manager and non-manager culture ratings are separate variables, with managers and non-managers arbitrarily ordered and 'missing' values coded -999 as follows:

CC_M	CC_{NM}	*QI*	*Org*
2	6	5	1
4	8	2	1
-999	9	4	1
-999	-999	5	1
-999	-999	7	1

1	4	1	2
2	6	2	2
-999	-999	3	2
-999	-999	5	2.

Setting up the data this way illustrates why the within-organization part of the MLPM is irrelevant—the CC_M and CC_{NM} scores come from different people and have no relationship within any given organization. Conversely, the data make clear why the between-organization part of the model is of interest—the model-estimated averages along each variable accurately represent manager *CC*, non-manager *CC*, as well as overall *QI* for an entire organization. In turn, the data illustrate why all relationships are at the organization level of analysis even though the predictors are measures of organizational groups' standings—each organizational group has a standing for each organization. Further with a full-information maximum likelihood or a Bayes estimator the arbitrary missingness is irrelevant for organization-level estimates.

Appendix B

Below is Mplus code for an MLPM with QI, CCm, CCnm, and Size variables as described in the text. Statements after a '!' are comments about input commands and are ignored by Mplus:

```
DATA: File is Data.dat;
VARIABLE: Names are Hospital QI CCm CCnm Size; Usevariables are QI CCm CCnm Size;
Cluster is Hospital; Between are Size; Missing are all (-999); ! Arbitrary missing value flag -999
ANALYSIS: ! A robust full-information maximum-likelihood estimator is used by default
Type = twolevel random; ! 'Random' is a command required to estimate latent interactions
Algorithm = integration; ! Numerical integration is required in the presence of latent interactions
MODEL:
%WITHIN% ! No need to specify a model within-organizations (variances estimated by default)
%BETWEEN% ! The between-organization model contains all parameters of interest
fCCm by CCm@1; fCCnm by CCnm@1; CCm@0 CCnm@0; ! Puts latent variables 'behind'
! random intercepts to allow using 'XWITH' to form latent squared/interaction terms as follows:
CCm2 | fCCm XWITH fCCm; ! Squares manager cultural content
CCmCCnm | fCCm XWITH fCCnm; ! Interaction term for managers and non-managers
CCnm2 | fCCnm XWITH fCCnm; ! Squares non-manager cultural content
QI on ! Regression equation as in Equation 7 with matching labels for beta terms as follows:
fCCm (beta12)
fCCnm (beta13)
CCm2 (beta14)
CCmCCnm (beta15)
CCnm2 (beta16)
```

```
Size;

[CCm@0 CCnm@0]; ! Sets grand means to zero, with latent variable means for these as follows:

[fCCm] (muCCm); [fCCnm] (muCCnm); ! Labels ‘mu’ reflect Greek terms found in Equation 7

MODEL CONSTRAINT:

New(a1 a2 a3 Delta CCm0 CCnm0 p10 p11 SQRT p11test); ! Creates new parameters

! that are labeled as in the Results section when they appear in the text, for additional details

! see Edwards & Parry (1993) and Edwards (1994). Note: Do not use parameters below for

! hypothesis testing, only to understand response surface statistics. For information on hypothesis

! testing see Appendix B.

a1 = beta12 + beta13; ! Slope along line of congruence, or Hypothesis 1

a2 = beta14 + beta15 + beta16; ! Curve along line of congruence, or Hypothesis 1

Delta = muCCm - muCCnm; ! Difference in grand-means, or Hypothesis 2

a3 = beta14 - beta15 + beta16; ! Curve along line of incongruence, or Hypothesis 3

CCm0 = (Beta13*Beta15 - 2*beta12*beta16)/(4*beta14*beta16 - beta15**2); ! Stationary

! point for CCm

CCnm0 = (Beta12*Beta15 - 2*beta13*beta14)/(4*beta14*beta16 - beta15**2); ! Stationary

! point for CCnm

0 = ((Beta14 - Beta16)**2 + Beta15**2) - SQRT**2; ! Defines SQRT as the square root of

! ((Beta14 - Beta16)**2 + Beta15**2), because subtracting SQRT**2 from this is set to 0

p10 = CCnm0 - p11*CCm0; ! First principle axis intercept

p11 = (Beta16 - Beta14 + SQRT)/Beta15; ! First principle axis slope

p11test = p11 - 1; ! Allows testing first principle axis slope’s difference from 1

OUTPUT: TECH1 TECH3 TECH5; ! Requests specific Mplus technical output
```

Appendix C

Below is Mplus syntax for generating 10,000 parameter estimates for $\beta_{12} - \beta_{16}$ from Equation 7 (see Table 2 for results). After running this syntax, results can be loaded into Excel or R in order to compute the response surface statistics for each of the 10,000 sets of estimated parameters (formulas for these are described above but also by Edwards and Parry [1993] and Edwards [1994]). Indeed, any combinations of parameters $\beta_{12} - \beta_{16}$ can then be tested by computing them for each of the 10,000 sets of estimated parameters. All 95% confidence intervals can be then be examined by sorting each response surface statistic or other combination of parameter estimates by its magnitude and then eliminating the first and last 250 observations. The syntax is:

```
MONTECARLO:
NAMES ARE beta12 beta13 beta14 beta15 beta16;
NOBSERVATIONS = 10000;
REPSAVE = ALL;
SAVE = MonteCarlo.dat;
MODEL POPULATION:
[beta12*.548 beta13*-.313 beta14*-.473 beta15*.872 beta16*-.412]; ! Sets population means for
! these variables equal to parameter estimates as shown in Table 2
beta12*.095 beta13*.089 beta14*.022 beta15*.078 beta16*.018; ! Sets variances of these
! variables equal to their asymptotic variance (i.e., the square of their SEs in Table 2)
beta12 with beta13*-.086 beta14*-.042 beta15*.081 beta16*-.038; ! Asymptotic covariances
beta13 with beta14*.039 beta15*-.078 beta16*.037; ! Asymptotic covariances
beta14 with beta15*-.038 beta16*.016; ! Asymptotic covariances
beta15 with beta16*-.034; ! Asymptotic covariance
```

References

Aarons, G. A., & Sawitzky, A. C. (2006). Organizational climate partially mediates the effect of culture on work attitudes and staff turnover in mental health services. *Administration and Policy in Mental Health and Mental Health Services Research*, *33*, 289–301.

Aguinis, H., Gottfredson, R. K., & Culpepper, S. A. (2013). Best-practice recommendations for estimating cross-level interaction effects using multilevel modeling. *Journal of Management, 39,* 1490-1528.

Armenakis, A. A., Harris, S. G., & Mossholder, K. W. (1993). Creating readiness for change. *Human Relations*, *46*, 681-703.

Axelrod, R. (1984). *The evolution of cooperation*. New York: Basic Books.

Barley, S. R., Meyer, G. W., & Gash, D. C. (1988). Cultures of culture: Academics, practitioners and the pragmatics of normative control. *Administrative Science Quarterly*, *33*, 24-60.

Barsness, Z. I., Shortell, S. M., Gillies, R. R., Hughes, E. F., O'Brien, L., Bohr, D., Izui, C. & Kralovec, P. (1993). The quality march. *Hospitals and Health Networks, 5*, 52-55.

Beisanz, J. C., Falk, C. F., & Savalei, V. (2010). Assessing meditational models: Testing and interval estimation for indirect effects. *Multivariate Behavioral Research, 45*, 661-701.

Bezrkova, K., Thatcher, S. M. B., Jehn, K. A., & Spell, C. S. (2012). The effects of alignments: Examining faultlines, organizational cultures, and performance. *Journal of Applied Psychology*, *97*, 77-92.

Birkinshaw, J., Hamel, G., & Mol, M.J. (2008). Management innovation. *Academy of Management Review*, *33*, 825-845.

Bliese, P. (2000). Within-group agreement, non-independence, and reliability. In K. Klein & S. Kozlowski (Eds.), *Multi-level theory, research, and methods in organizations* (pp. 349-

381). San Francisco, CA: Jossey-Bass.

Buenger, V., Daft, R. L., Conlon, E. J., & Austin, J. (1996). Competing values in organizations: Contextual influences and structural consequences. *Organization Science, 7*, 557-576.

Burke, C. S., Sims, D. E., Lazzara, E. H., & Salas, E. (2007). Trust in leadership: A multi-level review and integration, *Leadership Quarterly*, *18*, 606–632.

Burton, R M., Lauridsen, J., & Obel, B. (2004). The impact of organizational climate and strategic fit on firm performance. *Human Resource Management*, *43*, 67–82.

Cameron, K. S., & Quinn, R. E. (2006). *Diagnosing and changing organizational culture: Based on the Competing Values Framework*. San Francisco, CA: Jossey-Bass.

Champy, J. (1995). *Reengineering management: The mandate for new leadership*. New York, NY: HarperBusiness.

Chang, F. S., & Weibe, H. A. (1996). The ideal culture profile for total quality management: A competing values perspective. *Engineering Management Journal*, *8*, 19-26.

Corley, K. G. (2004). Defined by aour strategy or our culture? Hierarchical differences in perceptions of organizational identity and change. *Human Relations*, *57*, 1145–1177.

Cronbach, L. J., & Webb, N. (1975). Between-class and within-class effects in a reported aptitude × treatment interaction: Reanalysis of a study by G. L. Anderson. *Journal of Educational Psychology, 67,* 717-724.

Enders, C. K., & Tofighi, D. (2007). Centering predictor variables in cross-sectional multilevel models: A new look at an old issue. *Psychological Methods, 12*, 121-138.

Deal, T. E., & Kennedy, A. A. (1982). *Corporate cultures*. Reading, MA: Addison-Wesley.

DeCelles, K. A., Tesluk, P. E., & Taxman, F. S. (2013). A field investigation of multilevel cynicism toward change. *Organization Science*, *24*, 154-171.

Detert, J. R., Schroeder, R. G., & Mauriel, J. J. (2000). A framework for linking culture and improvement initiatives in organizations. *Academy of Management Review*, *25*, 850-863.

Devos, G., Buelens, M., & Bouckenooghe, D. (2007). Contribution of content, context, and process to understanding openness to organizational change: Two experimental studies. *Journal of Social Psychology*, *147*, 607-629.

Dirks, K. T., & Ferrin, D. L. (2001). The role of trust in organizational settings. *Organization Science*, *12*, 450-467.

Edwards, J. R. (1994). The study of congruence in organizational behavior research: Critique and a proposed alternative. *Organizational Behavior and Human Decision Processes*, *58*, 51-100.

Edwards, J. R., & Cable, D. M. (2009). The value of value congruence. *Journal of Applied Psychology*, *94*, 654-677.

Edwards, J. R., & Parry, M. E. (1993). On the use of polynomial regression equations as an alternative to difference scores in organizational research. *Academy of Management Journal*, *36*, 1577–1613.

Eisenhardt, K. M., & Graebner, M. E. (2007). Theory building from cases: Opportunities and challenges. *Academy of Management Journal, 50*, 25-32.

Erdogan, B., Liden, R. C., & Kraimer, M. L. (2006). Justice and leader–member exchange: The moderating role of organizational culture. *Academy of Management Journal*, *49*, 395–406.

Evan, W. M. (1977). Hierarchy, alienation, commitment, and organizational effectiveness. *Human Relations*, *30*, 77-94.

Field, C. A., & Welsh, A. H. (2007). Bootstrapping clustered data. *Journal of the Royal*

Statistical Society, B, 69, 369-390.

Finkelstein, S. & Hambrick, D. (1996). *Strategic leadership: Top executives and their effects on organisations*. Minneapolis: West Publishing.

Flynn, F. J., & Chatman, J. A. (2001). Strong cultures and innovation: Oxymoron or opportunity? In C. L. Cooper, S. Cartwright, & P. C. Earley (Eds.), *The international handbook of organizational culture and climate* (pp. 263-287). New York, NY: Wiley.

Fulmer, C. A. & Gelfand, M. J. (2012). At what level (and in whom) we trust: Trust across multiple organizational levels. *Journal of Management*, *38*, 1167-1230.

Geldhof, G. J., Preacher, K. J., & Zyphur, M. J. (2014). Reliability estimation in a multilevel confirmatory factor analysis framework. *Psychological Methods, 19*, 72-91.

Gerstner, C. R., & Day, D. V. (1997). Meta-analytic review of leader-member exchange theory: Correlates and construct issues. *Journal of Applied Psychology*, *82,* 827-844.

Gibson, C. B., Cooper, C. D., & Conger, J. A. (2009). Do you see what we see? The complex effects of perceptual distance between leaders and teams. *Journal of Applied Psychology, 94*, 62-76.

Gillespie, N. A., & Mann, L. (2004). Transformational leadership and shared values: the building blocks of trust. *Journal of Managerial Psychology*, *19*, 588-607.

Glisson, C., & James, L. R. (2002). The cross-level effects of culture and climate in human service teams. *Journal of Organizational Behavior, 23*, 767–794.

Golsorkhi, D., Rouleau, L., Seidl, D., & Vaara, E. (Eds.) (2010). *Cambridge handbook of strategy as practice*. Cambridge: Cambridge University Press.

Hammer, M., & Champy, J. (1993). *Reengineering the corporation: A manifesto for business revolution*. New York, NY: HarperBusiness.

Hartnell, C. A., Ou, A. Y., & Kinicki, A. (2011). Organizational culture and organizational effectiveness: A meta-analytic investigation of the Competing Values Framework's theoretical suppositions. *Journal of Applied Psychology*, *96,* 677–694.

Hill, N. S., Seo, M., Kang, J. H., & Taylor M. S. (2012). Building employee commitment to change across organizational levels: The influence of hierarchical distance and direct managers' transformational leadership. *Organization Science*, *23,* 758-777.

Hofmann, D. A., & Gavin, M. B. (1998). Centering decisions in hierarchical linear models: Implications for research in organizations. *Journal of Management, 24,* 623-641.

Huang, J. C., Newell, S., Galliers, R. D., & Pan, S. (2003). Dangerous liaisons? Component-based development and organizational subcultures. *IEEE Transactions on Engineering Management*, *50*, 89-99.

Jansen, K. J., & Kristof-Brown, A. L. (2005). Marching to the beat of a different drummer: Examining the impact of pacing congruence. *Organizational Behavior and Human Decision Processes, 97,* 93-105.

Jones, G. R., & George, J. M. (1998). The experience and evolution of trust: Implications for cooperation and teamwork. *Academy of Management Review*, *23*, 531-546.

Jones, M. C., Cline, M., & Ryan, S. (2006). Exploring knowledge sharing in ERP implementation: An organizational culture framework. *Decision Support System*, *41*, 411-434

Jones, R. A., Jimmieson, N. L., & Griffiths, A. (2005). The impact of organizational culture and reshaping capabilities on change implementation success: The mediating role of readiness for change. *Journal of Management Studies, 42*, 361-386.

Khazanchi, S., Lewis, M. W., & Boyer, K. K. (2007). Innovation-supportive culture: The impact of organizational values on process innovation. *Journal of Operations Management, 25*, 871–884.

Klein, A., & Moosbrugger, H. (2000). Maximum likelihood estimation of latent interaction effects with the LMS method. *Psychometrika, 65*, 457-474.

Klein, A. G., Schermelleh-Engel, K., Moosbrugger, H., & Kelava, A. (2009). Spurious interaction effects. In T. Teo & M. S. Khine (Eds.), *Structural equation modeling in educational research: Concepts and applications*. Amsterdam, NL: Sense Publishers.

Kumar, N., Stern, L. W., & Anderson, J. C. (1993). Conducting interorganizational research using key informants. *Academy of Management Journal, 36,* 1633-1651.

Lewicki, R. I., McAllister, D. J., & Bies, R. J. (1998). Trust and distrust: New relationships. *Academy of Management Review*, *23*, 438-458.

Liao, H., Toya, K., Lepak, D. P., & Hong, Y. (2009). Do they see eye to eye? Management and employee perspectives of high-performance work systems and influence processes on service quality. *Journal of Applied Psychology, 94,* 371-391.

Lüdtke, O., Marsh, H. W., Robitzsch, A., Trautwein, U., Asparouhov, T., & Muthén, B. (2008). The multilevel latent covariate model: A new more reliable approach to group-level effects in contextual studies. *Psychological Methods, 13,* 203-229.

Marsh, H. W., Lüdtke, O., Robitzsch, A., Trautwein, U., Asparouhov, T., Muthén, B. O., & Nagengast, B. (2009). Doubly-latent models of school contextual effects: Integrating multilevel and structural equation approaches to control measurement and sampling error. *Multivariate Behavioral Research, 44,* 764-802.

Mathieu, J. E., Aguinis, H., Culpepper, S. A., & Chen, G. (2012). Understanding and estimating the power to detect cross-level interaction effects in multilevel modeling. *Journal of*

Applied Psychology, 97, 951-966.

Matta, F. K., Scott, B. A., Koopman, J., & Conlon, D. E. (in press). Does seeing "eye to eye" affect work engagement and OCB? A role theory perspective on LMX agreement. *Academy of Management Journal*.

Moosbrugger, H., Schermelleh-Engel, K., Kelava; A. & Klein, A. G. (2009). Testing multiple nonlinear effects in structural equation modeling: A comparison of alternative estimation approaches. In T. Teo & M. S. Khine (Eds.), *Structural equation modeling in educational research: Concepts and applications*. Rotterdam, NL: Sense Publishers.

Muthén, B., & Asparouhov, T. (2003). Modeling interactions between latent and observed continuous variables using maximum-likelihood estimation in Mplus. *Mplus Web Notes, 6,* 1-9.

Muthén, B., & Asparouhov, T. (2008). *Growth mixture modeling: Analysis with non-Gaussian random effects*. In G. Fitzmaurice, M. Davidian, G. Verbeke, & G. Molenberghs (Eds.), Longitudinal data analysis (pp. 143–165). Boca Raton, FL: Chapman & Hall/CRC.

Muthén, L. K., & Muthén, B. O. (1998-2012). *Mplus User's Guide* (7th ed.). Los Angeles, CA: Muthén and Muthén.

Oreg, S., & Sverdlik, N. (2011). Ambivalence toward imposed change: The conflict between dispositional resistance to change and the orientation toward the change agent. *Journal of Applied Psychology*, *96,* 337-349.

O'Reilly, C. A. (1989). Corporations, culture, and commitment: Motivation and social control in organizations. *California Management Review, 31*, 9-25.

O'Reilly, C. A., & Chatman, J. A. (1996). Culture as social control: Corporations, culture and commitment. *Research in Organizational Behavior, 18*, 157–200.

Ostroff, C., Kinicki, A. J., & Muhammad, R. S. (2012). Organizational culture and climate. In N. Schmitt, & S. Highhouse (Eds.), *Handbook of Psychology, I/O Psychology*, (Vol. 12, pp. 643-676). New York, NY: Wiley and Sons.

Ostroff, C., Shin, Y., & Kinicki, A. J. (2005). Multiple perspectives of congruence: Relationships between value congruence and employee attitudes. *Journal of Organizational Behavior*, *26*, 591-623.

Ouchi, W. (1981). *Theory Z: How American business can meet the Japanese challenge*. Reading, MA: Addison-Wesley.

Peters, T., & Waterman, R. H. (1982). *In search of excellence*. New York, NY: Harper and Row.

Prajogo, D. I., & McDermott, C. M. (2005). The relationship between total quality management practices and organizational culture. *International Journal of Operations and Production Management, 25*, 1101-1122.

Preacher, K. J., & Selig, J. P. (2012). Advantages of Monte Carlo confidence intervals for indirect effects. *Communication Methods and Measures, 6,* 77-98.

Preacher, K. J., Zhang, Z., & Zyphur, M. J. (in press). Multilevel structural equation models for assessing moderation within and across levels of analysis. *Psychological Methods*.

Preacher, K. J., Zyphur, M. J., & Zhang, Z. (2010). A general multilevel SEM framework for assessing mediation. *Psychological Methods, 15*, 209-233.

Putnam, H. (2002). *The collapse of the fact/value dichotomy and other essays*. Cambridge, MA: Harvard University Press.

Quinn, R. E. (1988). *Beyond rational management*. San Francisco, CA: Jossey-Bass.

Raudenbush, S. W. (1989a). “Centering” predictors in multilevel analysis: Choices and consequences. *Multilevel Modelling Newsletter, 1,* 10-12.

Raudenbush, S. W. (1989b). A response to Longford and Plewis. *Multilevel Modelling Newsletter, 1*, 8-11.

Raudenbush, S. W., & Bryk, A. S. (1986). A hierarchical model for studying school effects. *Sociology of Education, 59*, 1-17.

Raudenbush, S. W., & Bryk, A. S. (2002). *Hierarchical linear model: Applications and data analysis methods* (2nd ed.). Thousand Oaks, CA: Sage.

Rousseau, D. M., & Tijoriwala, S. A. (1999). What's a good reason to change? Motivated reasoning and social accounts in promoting organizational change. *Journal of Applied Psychology*, *84*, 514-528.

Schein, E. H. (2004). *Organizational Culture and Leadership* (3rd ed.). San Francisco, CA: Jossey-Bass.

Schriesheim, C. A., Castro, S. L., Zhou, X., & Yammarino, F. J. (2001). The folly of theorizing "A" but testing "B": A selective level-of-analysis review of the field and a detailed leader-member exchange illustration. *Leadership Quarterly, 12,* 515-551.

Shadish, W., Cook, T., & Campbell, D. (2002). *Experimental & quasi-experimental designs for generalized causal inference*. Boston: Houghton Mifflin.

Short, J. C., Ketchen, D. J., & Palmer, P. B. (2002). The role of sampling in strategic management research on performance: a two-study analysis. *Journal of Management, 28,* 363-385.

Shortell, S.M., O'Brien, J. L., Carman, J. M., Foster, R. W., Hughes, E. F. X., Boerstler, H., & O'Connor, E. J. (1995). Assessing the impact of continuous quality improvement/total quality management: Concept versus implementation. *Health Services Research, 30,* 377-401.

Sin, H.-P., Nahrgang, J. D., & Morgeson, F. P. (2009). Understanding why they don't see eye to eye: An examination of leader–member exchange (LMX) agreement. *Journal of Applied Psychology, 94,* 1048-1057.

Sitkin, S. B. & Roth, N. L. (1993). Explaining the limited effectiveness of legalistic 'remedies' for trust/distrust. *Organization Science*, *4,* 367-392.

Sonpar, K., Handelman, J. M., & Dastmalchian, A. (2009). Implementing new institutional logics in pioneering organizations: The burden of justifying ethical appropriateness and trustworthiness. *Journal of Business Ethics*, *90*, 345-359.

Stackman, R. W., Pinder, C. C., & O'Connor, P. E. (2000). Values lost: Redirecting Research on values in the workplace. In N. Ashkanasy, C. Wilderom, & M. Peterson (Eds.), *The handbook of organizational culture and climate* (pp. 37-55). Thousand Oaks, CA: Sage Publications.

Tannenbaum, A. S., Kavcic, B., Rosner, M., Vianello, M., & Wieser, G. (1974). *Hierarchy in organizations*. San Francisco, CA: Jossey-Bass.

Tannenbaum, A. S., & Rozgonyi, T. (1986). *Authority and reward in organizations: An international research*. Ann Arbor, MI: Survey Research Center, Institute for Social Research, University of Michigan.

Trice, H. M., & Beyer, J. M. (1993). *The culture of work organizations*. Englewood Cliffs, NJ: Prentice-Hall.

Tyler, B. B., & Gnyawali, D. R. (2009). Managerial collective cognitions: An examination of similarities and differences of cultural orientations'. *Journal of Management Studies*, *46*, 93-126.

Westphal, J. D., Gulati, R., & Shortell, S. M. (1997). Customization or conformity? An institutional and network perspective on the content and consequences of TQM adoption. *Administrative Science Quarterly*, *42*, 366-394.

Ybema, S. B. (1997). Telling tales: Contrasts and commonalities within the organization of an amusement park - confronting and combining different perspectives. In S. Sackmann (Ed.), *Cultural complexity in organizations: Inherent contrasts and contradictions* (pp. 160-186). Thousand Oaks, CA: Sage Publications.

Zammuto, R. F., & Krakower, J. Y. (1991). Quantitative and qualitative studies of organizational culture. *Research in Organizational Change and Development*, *5*, 83-114.

Zammuto, R. F., & O'Connor, E. J. (1992). Gaining advanced manufacturing technology's benefits: The roles of organization design and culture. *Academy of Management Review*, *17*, 701-728.

Table 1

Descriptive Statistics and Correlations

	M	*SD*	*ICC(1)*	*1*	*2*	*3*	*4*
1. Size	220.90	173.34	----	----	-0.28	-0.37	-0.60
2. QI	3.34	0.62	0.08	-0.09	(0.99)	0.56	0.70
3. CC_M	53.63	19.01	0.16	-0.13	0.41	(0.79)	0.69
4. CC_{NM}	44.60	22.66	0.13	-0.13	0.53	*	(0.79)

Notes. Descriptive statistics for the variables used in the study; diagonal entries in parentheses are estimated reliabilities as α; values below the diagonal are for the full dataset (within + between hospital data), meaning the conventional zero-order correlations; the data above the diagonal are the correlations among the means for each hospital (estimates of the between-hospital correlations that are used for the response surface analysis); *ICC* = intra-class correlation, or ICC(1), as the model-estimated proportion of between-hospital variation to total variation; Size = number of beds at a hospital; *QI* = degree of quality improvement implementation; CC_M = managers' cultural content; CC_{NM} = non-managers' cultural content; * indicates that variables only have a meaningful relationship between hospitals.

Table 2

Multilevel Latent Polynomial Regression Results

	Multilevel Latent Polynomial Regression		
	Parameter Estimate	SE	*p*-value
QI regressed on:			
CC_M	0.55	0.31	0.08
CC_{NM}	-0.31	0.30	0.30
CC_M^2	-0.47	0.15	<0.01
CC_M*CC_{NM}	0.87	0.28	<0.01
CC_{NM}^2	-0.41	0.14	<0.01
Size	0.03	0.01	0.01
Intercepts/Means			
QI	3.38	0.15	<0.01
CC_M	0.62	0.11	<0.01
CC_{NM}	-0.43	0.11	<0.01
	Response Surface Parameters and Confidence Intervals		
	2.5%	Parameter Estimate	97.5%
a_1	0.02	0.24	0.45
a_2	-0.17	-0.01	0.14
a_3	-2.89	-1.76	-0.68
p_{10}	-5.38	-0.51	5.10
p_{11}	0.31	1.07	1.51
Δ	0.94	1.05	1.16

Notes. *QI* = quality improvement implementation; CC_M = managers’ cultural content scores; CC_{NM} = non-managers’ cultural content scores; *Size* = number of beds in each hospital; a_1 = slope along line of congruence; a_2 = curvature along line of congruence; a_3 = curvature along line of incongruence; p_{10} = y-intercept for the first principal axis; p_{11} = slope for the first principal axis; Δ = difference between manager and non-manager grand-mean cultural content scores ($\mu_{CC_M} - \mu_{CC_{NM}}$).

Table 3

Comparison of Manager and Non-manager Mean CVF Quadrant Scores

a. Congruent subsample, n = 33

CVF Quadrant	Managers	Non-managers	Correlations
Human Relations	37	34[a]	0.89**
Open Systems	17	16	0.81**
Internal Process	23	27 [a]	0.87**
Rational Goal	22	22	0.82**

b. Incongruent subsample, n = 34

CVF Quadrant	Managers	Non-managers	Correlations
Human Relations	37	27 [a,b]	0.62**
Open Systems	18	15 [a]	0.51**
Internal Process	22	33 [a,b]	0.30
Rational Goal	23	24 [a,b]	0.64**

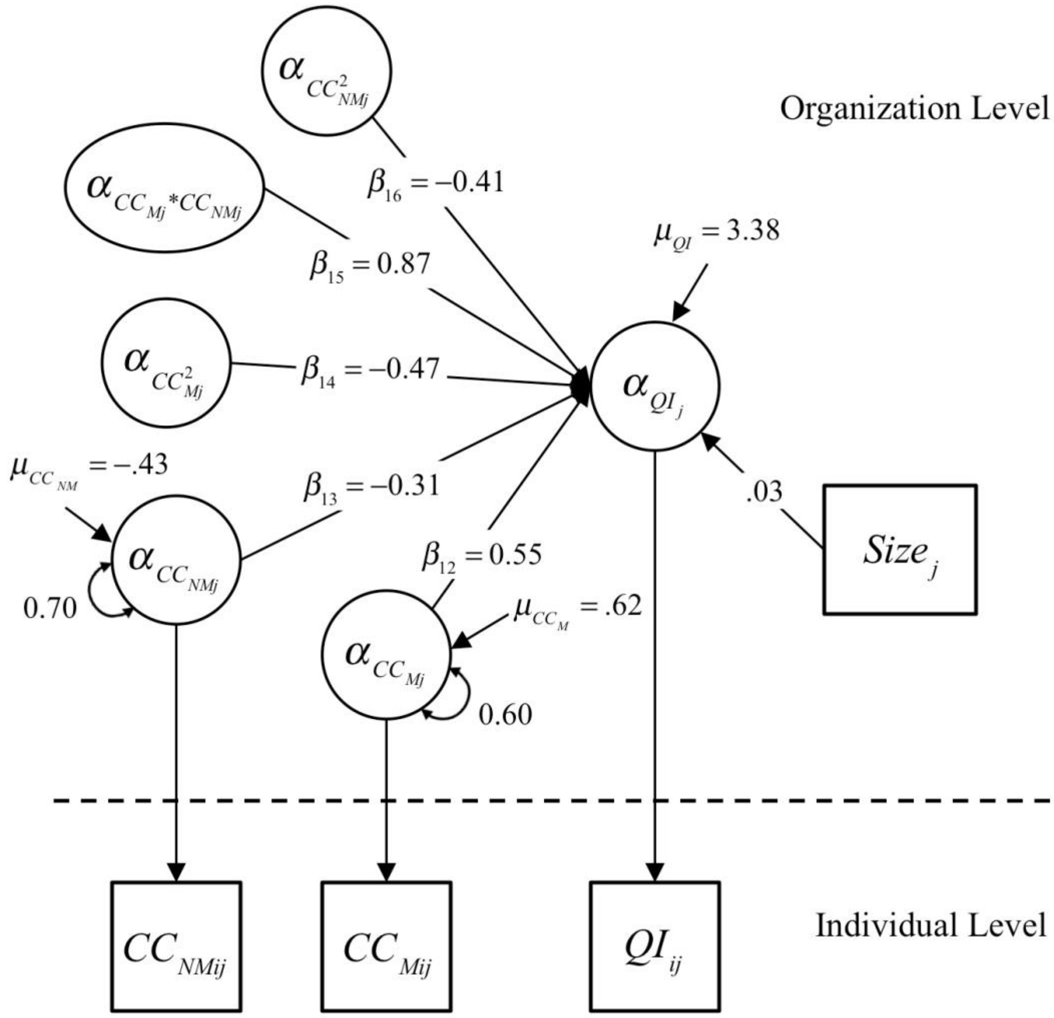
** $p < 0.01$

[a]Significant difference (*t*-test) between manager and non-manager CVF quadrant scores within subsample ($p < 0.05$)

[b]Signficant difference (*t*-test) between non-managers' CVF quadrant scores across subsamples ($p < 0.05$)

Figure 1

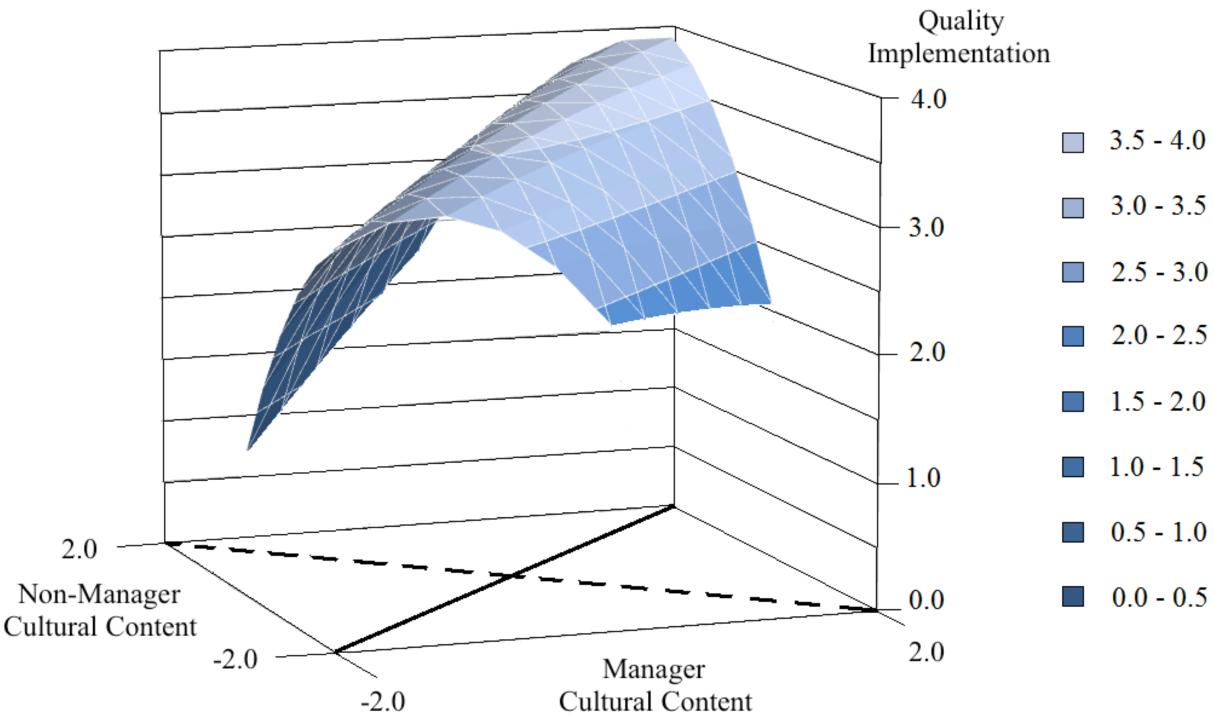
Multilevel Latent Polynomial Regression Model



Notes: Diagram of structural and measurement relationships for study variables; rectangles are observed and circles are latent; single-headed arrows connecting two variables are regression paths; single-headed arrows attached to a single variable are intercepts/means, and double-headed arrows are variances; all variables and parameters are as defined in Equations 6 and 7, wherein CC_M = cultural content for managers, CC_{NM} = cultural content for non-managers, *QI* = quality implementation, *Size* = number of hospital beds; αs are random intercepts; μs are grand means.

Figure 2

Response Surface Relating Manager and Non-manager Cultural Content Perceptions and QI



Notes: Response surface relating managers and non-managers cultural content ratings with degree of quality improvement implementation. Solid line is the line of congruence; thin dashed line is the line of incongruence.