Appendix B: Technical Appendix on Hierarchical Linear Models (HLM)

Rationale

Multilevel modeling is a statistical approach used to analyze nested data, where observations are embedded within different contexts or settings. Observations that are nested within the same setting are not statistically independent (i.e., all observations in one setting are exposed to the same environmental influences). Multilevel modeling techniques have been developed to address this lack of independence among observations (Raudenbush & Bryk, 2002).

Data may be nested at several levels. For example, individuals may be nested within an organizational setting, and the organization itself may be nested within a market. Most multilevel studies consider 2 or 3 levels. The first level in a multilevel model is the level at which the dependent variable operates. For example, in our study our dependent variables were measures of physician satisfaction with the organizational and managerial capabilities of the groups in which they work. The level-1 model may also incorporate independent variables, in this case individual physician characteristics. In our study, the second level contains independent variables that operate at the medical group level. Individual physician respondents are not independent because they are nested within medical groups. Multilevel models may also be used to estimate growth curves, or time series analysis, where the first level would be time and the second level could be individuals nested within particular time frames.

With nested data, clustering issues need to be addressed before performing multivariate analyses examining the effects of characteristics of the setting on individual level outcomes (e.g., in our study we examined the relationship between organizational culture, a contextual or setting measure, on physician satisfaction with the managerial and organizational capabilities of the groups in which they work, an individual outcome). Ordinary least squares regression may produce inflated standard errors of the regression coefficients. Resulting tests to assess whether the coefficients are significantly different from zero may therefore be invalid, although the coefficients themselves will be correctly estimated.

Traditionally, researchers have addressed clustering issues by: 1) aggregating their data to the level of the setting (e.g., in our study we could have looked at average physician satisfaction and related it to organizational culture), or 2) correcting the standard errors, with an econometric adjustment like the Huber correction. Multilevel modeling techniques such as Hierarchical Linear Modeling (HLM) are designed to preclude having to aggregate data to a higher level of analysis. Aggregation could potentially decrease the variation in a dependent variable and may lead to Type II errors, concluding that there is no statistically significant relationship when in fact there is. Employing a standard econometric adjustment, like a Huber correction, does not address the underlying structure of the data, or the degree to which particular levels of analysis explain the variation in the dependent variable. Multilevel modeling allows researchers to structure their data in ways that are conceptually appropriate and allows assessment of the contribution of each level of analysis to explaining variation in the dependent variable.

In a multilevel analysis, variance in the dependent variable is decomposed into within and between group components. Two equations result; a within-unit model:

$$Y_{ij} = \beta_{0j} + r_{ij}$$

and a between-unit model:

$$\beta_{0j}=\gamma_{00} + u_{0j}$$

Suppose Y_{ij} is the response variable, physician satisfaction. The within-unit model indicates that group member values on physician satisfaction vary around the unit mean, β_{0j}. The level-1 random effect, r_{ij} is normally distributed with homogenous variance across units, that is, $r_{ij} \sim N(0, \sigma^2)$. The between-unit model indicates that unit means on physician satisfaction vary around the grand mean, γ_{00}. The level-2 random effect, u_{0j}, is normally distributed with homogenous variance across units, that is, $u_{0j} \sim N(0, \tau_{00})$.

The above models are then extended to incorporate individual- and unit-level predictor variables as follows:

[1] Physician job satisfaction, $Y_{ij} = \beta_{0j} + \beta_{1j}(\text{perception of culture})_{ij} + \beta_{2j}(\text{age})_{ij} + \beta_{3j}(\text{gender})_{ij} + \beta_{4j}(\text{primary care})_{ij} + \beta_{5j}(\text{\%patients from HMOs \& PPOs})_{ij} + r_i$

Equation [1] illustrates that individual job satisfaction, occupational membership, gender and professional tenure are expected to explain a portion of the variance in individual staff member intention to quit within a unit.

Level-2 model

[2a] $\beta_{0j} = y_{00} + y_{01}(\text{organizational culture})_j + y_{02}(\text{group size})_j + y_{03}\ (\text{\%male})_j + y_{04}(\text{specialty group})_j + y_{05}(\text{multi-specialty group})_j + u_{0j}$

where $\beta_{1j} = y_{10}$, $\beta_{2j} = y_{20}$, $\beta_{3j} = y_{30}$, $\beta_{4j} = y_{40}$, $\beta_{5j} = y_{50}$ for the i^{th} physician in the j^{th} group

Equation [2a] reflects the hypothesized model to explain the variance in the intercept value (β_0) produced in the level-1 model.

The full multilevel model can also be expressed as a simple algebraic combination of the equations [1] and [2a].

Steps in Multilevel Modeling

The first step in performing multilevel modeling is to estimate the intra-class correlation (ICC) in the dependent variable of interest across groups. The ICC varies from 0 to 1. The closer the ICC is to 1, the greater the amount of between group variation, or within group correlation, in the dependent variable. A significant difference between groups supports using a multilevel model that includes group level predictor variables. A significant difference between groups would suggest that it is reasonable to continue building a multilevel model to explain between unit variation in physician satisfaction.

After determining the ICC, the next step in multilevel modeling is to examine a first level model, without group level predictor variables. A first level model incorporates predictor variables at the first level of analysis (the individual physician). The results of the level-1 model are used to determine whether the relationship between individual (i.e., physician) level variables and satisfaction vary by organizational unit (i.e., medical group). If the parameters do vary significantly by unit/organizational, the corresponding parameter variance can be modeled using unit/organizational level predictors.

Centering Decisions

The independent variables in multilevel models may be uncentered, centered according to the group that a particular observation is in, or grand mean centered (i.e., according to the mean for the overall sample). Hoffman (1998) outlines the three options and the implications for each decision, and reviews the work of others in this regard. In his paper Hoffman cites how Kreft, et al. (1995) demonstrated that uncentered data and grand mean centering "produced equivalent models" but that there may be slight advantages of using grand mean centered data over uncentered data with respect to limiting the possibility of multicollinearity. In this analysis, we have chosen to grand mean center all of the predictor variables. This not only allows for a more interpretable overall intercept term (the expected satisfaction of physicians with "average" level-1 predictors, like age, perception of culture, etc.), but also has implications for how the level-2 coefficients are interpreted. Grand mean centering allows us to examine the group level relationships between the level-2 predictors and physician satisfaction while controlling for the level-1 predictors. Uncentered data or group centered data do not allow for the adjustments of level-1 predictors when examining level-2 coefficients (Hofmann 1997).

<u>Fixed versus Random Effects</u>

A second critical decision is whether the slopes of the independent variables will be allowed to randomly vary across the higher order levels of analysis, or whether they should be fixed effects and not allowed to randomly vary. In HLM, modeling a slope is similar to testing an interaction term in Ordinary Least Squares (OLS) regression analysis.

[2b] $\beta_{1j} = \gamma_{10} + \gamma_{11}(\text{organizational culture})_j + \gamma_{12}(\text{group size})_j + \gamma_{13}(\text{\% male})_j + \gamma_{14}(\text{specialist group})_j + \gamma_{15}(\text{multi-specialist group})_j + u_{1j}$

[2c] $\beta_{2j} = \gamma_{20} \ldots\ldots \beta_{7j} = \gamma_{70}$

Equation [2b] reflects an example of a model to explain the variance in the slope value (β_1) produced in the level-1 model (equation [1] above). In other words, the variance in the relationship between, say, age and physician satisfaction (the β_1 slope) across units will be explained by level 2 variables – organizational culture, group size, %male, specialist group and multi-specialty group. Finally, equation [2c] indicates that the relationships between the remaining individual level variables (perception of culture, gender, primary care, and % patients from HMOs & PPOs) in the model and the dependent variable are not expected to vary significantly across units. Therefore the slope, or β value, represents the average slope across units.

As in the intercept model, the full multilevel model can also be expressed as a simple algebraic combination of the equations [1], [2a], [2b] and [2c]. The above equations illustrate that the intercept (β_0) and individual job satisfaction slope (β_1) are modeled as outcomes in the second level model.