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Chapter 5

Quantitative Methods for Studying Social Context in Multilevels and Through Interpersonal Relations

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The connection between a volume on the social organization of learning and a chapter with a title that begins with the words “Quantitative methods . . .” may not seem obvious, especially in view of the fact that so much of our recent socially grounded educational inquiry has been conducted within a qualitative or interpretive paradigm. In this chapter, I attempt to make as strong a case as possible for the importance of quantitative methods in understanding the social organization of learning. I want to argue that both at the level of macroanalysis (considering the effects of different levels of social organization, such as the district, school, and classroom) and at the level of microanalysis (examining relations among individuals in their primary social settings), quantitative methods can help us achieve important insights and understanding about the nature, causes, and consequences of social relations.

Schooling is a complex process because teachers, students, and administrators operate in a diverse set of social contexts.1 Although they may appear to be isolated in their classroom practices (Cusick, 1983; Hargreaves, 1993; Lortie, 1977), teachers are affected by their social contexts, as they are influenced by others’ orientations to teaching and classroom practices (e.g., Rowan, 1990; Trent, 1992; Wilson & Ball, 1991; Zeichner & Gore, 1989). Although principals may make many of the official decisions regarding school policies and practices (Callahan, 1962; Greenfield, 1975; Ingersoll, 1994; Levine & Lezotte, 1990; Smith, Prunty, & Dwyer, 1981), institutional contexts defined across most schools determine the parameters of decision making (Meyer & Rowan, 1977; Rowan, 1995), and relations among faculty and students help generate the organizational context in which many decisions are made (Bidwell & Quiroz, 1991; Firestone & Wilson, 1985; Fuller & Izu, 1986; Johnson, 1990; Lightfoot, 1983; Little, 1984; Rosenholtz, 1989). And though a school may have general policies or structures (Coleman et al., 1966; Peshkin, 1986; Shedd & Bacharach, 1991), the experience of each student, teacher, and administrator is unique, because each person’s social context is uniquely defined within and outside the school’s walls (Bidwell & Kasarda, 1980; Dreeben & Gamoran, 1986; Pallas, 1988; Sorensen & Hallinan, 1976).

The social contexts are complex because they are defined at multiple levels (Barr & Dreeben, 1977, 1983; Bidwell & Kasarda, 1980; Bray & Thomas, 1995; Keeves & Sellin, 1988; Oosthoek & van den Eeden, 1984) and through relations among a variety of people in a common setting (Barr & Dreeben, 1983; Bidwell

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& Kasarda, 1980; Dreeben & Barr, 1988; Epstein & Karweit, 1983; Gamoran, 1987; Lazersfeld & Menzel, 1961; Miskel & Ogawa, 1988; Staessens, 1993; Schein, 1985). Each individual—whether student, teacher, or administrator—experiences “multilevels” of the school as an institution, a unique organization, and a unique set of individual experiences. Institutionalized aspects of schooling include the authority of teachers, systems for grouping by ability, courses offered within departments, definitions of special education, and evaluation according to external criteria (e.g., standardized multiple-choice tests, portfolio assessment). These institutions are established outside of the school walls and, therefore, can be defined in terms of relations and processes of widely shared societal understandings of schooling (DiMaggio & Powell, 1991; Mehan, Hertweck, & Meihls, 1986; Meyer & Rowan, 1991; Waller, 1932). For example, Pallas, Entwisle, Alexander, and Stluka (1994) argue that “ability grouping is pervasive because it is taken for granted as a rational way to organize instruction to improve students’ achievement” (p. 29), even though students may be matched to groups through a nonrational process (DeLany, 1991; Riehl & Pallas, 1992). As teachers develop understandings of subject matter and expectations for learning, they too encounter institutionalized aspects of schooling that are defined beyond the walls of the school. For example, teachers’ approaches to teaching are affected by the subject they teach (Bidwell, Frank, & Quiroz, 1997; Grossman & Stodolsky, 1995), the sector in which they teach (Bryk, Lee, & Holland, 1993), and the values and norms associated with the socioeconomic status of the students they teach (Metz, 1990).

The school as an organization also affects the schooling experience. As members of a school interact and influence one another, they develop shared understandings, educational practices, and mechanisms for decision making (Bidwell et al., 1997; Bird & Little, 1986; Johnson, 1990; Lightfoot, 1983; Little, 1984; Rosenholtz, 1989; Rowan, 1990). For example, faculty, administrators, and students construct shared meanings of gender (Canada & Pringle, 1995; Hall & Sandler, 1982; Nias, 1989; see Brophy, 1985, for a review), with important effects on students’ achievement and attitudes (Lee, Marks, & Byrd, 1994). In the aggregate, these relations partly define the school as a unique organization that affects each person in the school (Alexander & Pallas, 1985; Barker & Gump, 1964; Barr & Dreeben, 1983; Bryk & Driscoll, 1988; Gamoran, 1987; Lazersfeld & Menzel, 1961; McDermott & Aron, 1978; Mehan et al., 1986; Miskel & Ogawa, 1988; Ogbu, 1978; Sarason, 1971; Schein, 1985; Spradley & McCurdy, 1972; Staessens, 1993). Gamoran (1991) refers to this as the additive model, in which schooling experiences equally affect each student.

But schooling experiences are unique for each individual, partly through the unique actions of other people to which each person is exposed and partly through the unique background experiences that each person brings to the school that frames the school experience (Bidwell & Kasarda, 1980; Murnane, 1975; Pallas, 1988; Sorensen & Hallinan, 1976; Summers & Wolfe, 1977). For example, students will encounter markedly different schooling experiences depending on the track to which they are assigned (Alexander, Cook, & McDill, 1978; Eder, 1981; Hansell & Karweit, 1983; Heyns, 1974; Oakes, 1985; Sorensen, 1984). Moreover, the institution of tracking
tends to reproduce existing differences in students’ prior experiences, which vary according to socioeconomic background or race (Bowles & Gintis, 1976; Hollingshead, 1949; Lee & Bryk, 1989; Oakes, 1985; Rosenbaum, 1976). Gamoran (1991) refers to this as the interactive model, in which the effects of schooling characteristics interact with student characteristics to shape schooling experiences.

Much of our understanding of the complexity of the organization of schooling comes from analyses of qualitative data. In particular, research has recently focused on the institutions of schooling as well as elements unique to teachers and classrooms within a school, thus differentiating the multilevels at which schooling occurs (e.g., Anstead & Goodson, 1993; Mehan, 1992; Riehl & Pallas, 1992). For example, micro-ethnographic analyses have characterized laws and cultural institutions that define the contexts for decisions regarding students’ needs for special education (e.g., Erickson & Shultz, 1982; Mehan, 1992; Mehan et al., 1986).

Traditional methods for quantitative analyses have a moderate capacity to address the complex process of schooling. Using the general linear model (i.e., regression and analysis of variance), one can estimate the effects of attributes of people on their schooling experiences, and, through multiple regression, one can control for important covariates. Furthermore, using terms representing the interaction of two attributes, one can model how effects of attributes vary across contexts (e.g., Hannaway & Talbert, 1993). But the interpretation of significance values based on distributional assumptions (i.e., parametric analyses) typically requires that error terms—the part of an outcome that cannot be explained by observed factors—be independent and identically distributed. This assumption is in direct contrast to the characterization of schools as complex organizations partially defined by relations among people affiliated with the school.

Until recently, most quantitative analyses including more than one person affiliated with a given school simply did not account for dependencies among the observations (e.g., Bowles & Gintis, 1976; Coleman et al., 1966; Dreeben & Gamoran, 1986; Epstein & Karwait, 1983; Kilgore & Pendleton, 1993). These analyses used models that did not represent the nested nature of the phenomena, with negative consequences for statistical inference (Bryk & Raudenbush, 1992). Others have met the statistical assumption of independent error terms by analyzing data aggregated to the school level; thus, they have eliminated the difficulty introduced by dependencies among observations within a single school (e.g., Hannaway & Talbert, 1993), by analyzing data from a few schools and accounting for school effects through fixed effects estimation (e.g., Hallinan, 1992), or by analyzing observations from different schools (e.g., Chew, 1992). Although we can learn of commonalities across schools from such data, theoretical and mathematical models built from these data necessarily ignore the complex processes within schools as organizations. In these cases, the statistical tail is doing the wagging.

In this chapter, I consider two recent advances in quantitative methods that can help us to understand schooling as a complex process. First, multilevel models help account for one source of dependency among teachers and students, the common schools with which they are affiliated. Multilevel models also can be
used to represent and estimate how characteristics of individuals covary according to school context. Second, quantitative analyses of social network data (e.g., who talks to whom or who influences whom) can help characterize and model the effects of interdependencies among the people in a school. In the next section, I illustrate the importance of multilevel models by reviewing work by Lee and Smith (1995) representing some of the effects of social contexts, such as student socioeconomic status and school engagement in restructuring, as well as the interaction of these two effects. I then discuss social network analysis as a way of identifying the intraschool processes that generate differences in social contexts of schooling. I conclude by calling for extensions of social network analysis to a multilevel framework so as to more adequately capture the social processes of schooling.

**MULTILEVEL MODELS: EFFECTS OF SOCIAL CONTEXTS AT THE INDIVIDUAL AND SCHOOL LEVELS**

In the preceding section, I distinguished between social context defined at the level of the school (in terms of shared understandings, school culture, decision making, etc.) and social context defined at the level of individuals (e.g., in terms of students’ socioeconomic background or the subject taught by a teacher). Effects at multiple levels can be addressed with multilevel models, and in this section I familiarize the reader with multilevel models through a discussion and graphical representation of Lee and Smith’s (1995) application estimating school and student effects on student achievement (for a full introduction to multilevel models, see Bryk & Raudenbush, 1992; Goldstein, 1995; Longford, 1993; Raudenbush & Bryk, 1988). I then discuss recent developments in multilevel models that have particular applications to the study of social contexts in schools.

Multilevel models, introduced in education in the 1980s, are ideally suited to incorporating features of social contexts defined at the level of the individual and school (Burstein, 1980; Goldstein, 1987; Raudenbush & Bryk, 1986, 1988). Indeed, many of the initial applications incorporated elements of both student context (e.g., socioeconomic status, curricular track placement) and school context (e.g., sense of community, size) (Bryk & Raudenbush, 1988; Lee & Bryk, 1989; Raudenbush & Bryk, 1986, 1988). Multilevel models expand the types of questions that can be asked by incorporating terms typically not specified in single-level models and provide more powerful tests and accurate estimates of effects at each level.

The relatively recent example in Lee and Smith (1995) represents the power of these analyses when combined with nationally representative data such as that from the National Educational Longitudinal Study (NELS). The following multilevel model represents a simplified version of one of the analyses conducted by Lee and Smith:

\[
\begin{align*}
\text{At the student level (level 1):} \\
\text{gain in achievement}_j &= \beta_{0j} + \beta_{1j} \text{ socioeconomic status}_j + r_{ij} \\
&= \gamma_{00} + \gamma_{01} \text{ PCR}_j + \gamma_{11} \text{ PCR}_j + u_{ij}, \\
\text{At the school level (level 2):} \\
\beta_{0j} &= \gamma_{00} + \gamma_{01} \text{ PCR}_j + u_{0j}, \text{ and} \\
\beta_{1j} &= \gamma_{10} + \gamma_{11} \text{ PCR}_j + u_{1j}.
\end{align*}
\]
Several features of the model are worthy of comment. First, unlike earlier models estimated on data from the High School and Beyond study, Lee and Smith were able to incorporate measures from NELS regarding prior achievement. Lee and Smith chose to incorporate two measures of achievement (measured in 8th and 10th grades) by defining their outcome as the gain in achievement over the 2-year period (the primary alternative would have been to use 8th-grade achievement as a covariate in a model of 10th-grade achievement).

Gain scores, or difference scores, have been much criticized as “unreliable” (e.g., Bereiter, 1963; Linn & Slinde, 1977; see Willett, 1988, for a review); more recently, however, the deficiencies of difference scores have been described as “perceived rather than actual, imaginary rather than real” (Willett, 1988, p. 367; see also Rogosa, Brandt, & Zimowski, 1982; Rogosa & Willett, 1983; Zimmerman, Brotohusodo, & Williams, 1981). The difference score is an unbiased measure of the true change in an outcome, a reasonable measure of growth when one has data from only two time points (Willett, 1988). Moreover Allison (1990, pp. 107–109) recommends the use of the difference score partially based on whether the pretest is unrelated to the “treatment.” In this case, the type of high school that a student experiences (the “treatment”) is more likely to depend on geography than on the student’s eighth-grade math achievement. (See also Willett, 1988, pp. 366–380, for a discussion of difference scores. See Plewis, 1991, or Friedkin & Thomas, 1997, for alternatives using pretest as a covariate. See Willms & Raudenbush, 1989, or Patterson, 1991, for alternatives using repeated cross-sectional designs.)

Next, note that the double subscript in the student-level model references observations for each student i in school j. The second subscript, j, effectively allows one to conceptualize a regression in each school j. Thus, on the right-hand side of the student-level model, we define \( \beta_0 \) and \( \beta_1 \) uniquely for each school j, and we write \( \beta_{0j} \) and \( \beta_{1j} \); \( \beta_{0j} \) represents the intercept in school j, thus capturing the unique average gain in achievement for students in school j (assuming that the predictor, socioeconomic status, is centered around the school mean socioeconomic status; see Bryk & Raudenbush, 1992, pp. 25–31, for a discussion of centering). Similarly, \( \beta_{1j} \) captures the unique relationship between socioeconomic status and gain in achievement in school j. Socioeconomic status, affecting the child’s context in the home, has consistently been shown to affect outcomes associated with schooling such as students’ aspirations, interest in school, and achievement (Apple, 1979; Bowles & Gintis, 1976; Eder, 1981; Gamoran, 1996; Hollingshead, 1949; Lee & Bryk, 1989; Lee & Smith, 1993).

Finally, the student-level model includes a unique error term for student i in school j, \( r_{ij} \), indicating that each student’s gain in achievement will not be perfectly predicted by the regression equation in his or her school. In most applications of multilevel models, the errors are assumed to be normally distributed and have constant variance, \( \sigma^2 \), across schools. This assumption is comparable to the assumption in the general linear model in that residual variation is assumed to be constant across units.

Moving to the school-level model, the intercept and regression slopes (in this case, \( \beta_{0j} \) and \( \beta_{1j} \)) are modeled as functions of school-level predictors (Burstein, 1980). Here Lee and Smith model school mean gains in achievement, represented
by $\beta_{0j}$, as a function of whether or not the school engages in practices consistent with restructuring (PCR). PCR is a recent reform in schools challenging many of the prevailing institutions of schooling that segregate faculty and students (Carnegie Council on Adolescent Development, 1989; Carnegie Task Force on Teaching as a Profession, 1986; Lee & Smith, 1993; National Commission on Excellence in Education, 1983; Weiss, 1995). In particular, Lee and Smith defined schools as engaging in PCR, practices consistent with traditional reform (PCT), or no reform practices on the basis of items indicating the extent to which the school challenged traditional organizational structure by encouraging interdisciplinary teaching, mixed-ability classes, staff problem solving, parent volunteers, flexible class times, cooperative learning, and so forth. Note that these distinctions are defined at the level of the school and, thus, are modeled on the average gain in achievement in the school.

The $u_{0j}$ term in the model for $\beta_{0j}$ represents the unique effect of school $j$ on student gains in achievement after the effect of PCR has been controlled. That is, it can be considered the error in the model for $\beta_{0j}$. One of the basic analyses involved in multilevel modeling is a comparison of the variation (referred to as $\tau_0$) of errors at the school level and the variation ($\sigma^2$) of errors at the student level.

A key aspect of the multilevel framework is that it facilitates the specification of interaction effects crossing school-level and individual-level factors. In this case, the relationship between socioeconomic status and gain in achievement in school $j$, represented by $\beta_{1j}$, is modeled as a function of whether or not the school engages in PCR. The research question here might be as follows: Does the effect of socioeconomic status on gain in achievement depend on whether or not a school engages in PCR? The $u_{1j}$ then represent the unique component of the $\beta_{1j}$ that cannot be attributed to whether or not the school engages in PCR.

Lee and Smith estimated models similar to those in Equation 1 for gains in mathematics achievement. In an initial model, Lee and Smith differentiated between variation at the student level and variation at the school level. They found that approximately 15% of the variation in gains in mathematics achievement was between schools. While modest, this amount is not inconsequential from a policy-making standpoint. First, schools may represent the most important institutional effect on achievement, with effects of other institutions more difficult to specify. Second, we can identify and therefore potentially change those aspects of schools that are linked to achievement. Still, as I turn to an interpretation of the effects of school organization, it is helpful to keep in mind that the school-level factors used by Lee and Smith can explain at most only 15% of the variation in student achievement.

Next, Lee and Smith found that, on average, students in PCR schools gained .86 more in standardized mathematics scores than students in schools that engaged in PCT ($\hat{\gamma}_{01} = .86, p < .001$). This is consistent with the argument that a school-level policy of restructuring can affect achievement, and the evidence is more powerful when one considers that the reported effect of PCR is net of controls for a host of other characteristics of schools (e.g., academic emphasis, course-taking patterns,
Lee and Smith also found that the relationship between socioeconomic status and achievement was not as strong in schools engaged in PCR as those engaged in PCT. In schools that engaged in PCR, a one-unit increase in socioeconomic status was estimated to be associated with an increase of .16 ($\hat{Y}_{10} + \hat{Y}_{11} = .38 - .22 = .16$) in mathematics achievement, while the effect was estimated at .38 ($\hat{Y}_{10} = .38$) in PCT schools (the difference in the two effects was established by testing the significance of $\hat{Y}_{11}$, which, in this case, indicated $p \leq .01$). Thus, the advantages of high socioeconomic status are greater in schools that have not actively broken down many of the barriers that segment students and teachers.

The regression lines representing the relationship between socioeconomic status and gain in mathematics achievement in 20 hypothetical schools (10 PCT and 10 PCR) shown in Figure 1 are based on the findings of Lee and Smith. For example, the regression line for School 1 is determined by the intercept ($\beta_{01} = 1.85$) and slope ($\beta_{11} = 1.4$, indicating that the expected gain in mathematics achievement increases 1.4 units for a 1-unit increase in socioeconomic status). In Figure 1, one can roughly observe that the average intercept and slope are different between the two types of schools. The intercepts, the predicted gains in mathematics achievement for an average student, are slightly higher in PCR schools than in schools engaging in PCT (note that three of the four highest intercepts are for PCR schools, while three of the four lowest intercepts are for schools engaging in PCT). Differences among the sets of slopes are more difficult to discern, although there are several PCT schools with relatively steep slopes.

Figure 1 also helps to differentiate the two sets of error terms. Clearly, students’ gains in achievement are not completely determined by any single aspect of their social contexts, in this case their socioeconomic status and the type of school they attend. Thus, the error term for Student 1 in School 1, $r_{11}$, is indicated as the deviation of the observation from the regression line, where the regression line in School 1 is given by $\beta_{01}$ and $\beta_{11}$ (to accurately represent the findings in Lee and Smith, the variance of the residuals in School 1 would have to be four times greater than the variance of the intercepts; the variance of the residuals is reduced in the figure for visual clarity). Equally as clear, the average level of gain in mathematics achievement and the relationship between gain in mathematics achievement and socioeconomic status are not completely determined by whether the school engages in PCR or PCT. Thus, the school-level errors are captured in the deviation of a given intercept, $u_{0j}$, from the overall average for that type of school, and errors in the school-level slopes are captured in the deviation of a given slope, $u_{1j}$, from the average slope for that type of school. Thus, we again observe two fundamental sources of variation in schooling effects: Those associated with students and those associated with schools.

Consideration of the differences in the regression lines between the two groups relative to the variation should serve as a caution against overinterpreting effects
FIGURE 1
Mathematics Gains by Socioeconomic Status Unique for Each School

Standardized Socioeconomic Status

-- -- -- PCR Schools

* indicates students in school 1

--- Traditional Reform Schools

\[ \hat{\beta}_{11} = 0.14 \]

\[ \hat{\beta}_{01} = 1.85 \]
found to be significant in large samples (there were 820 schools in the sample). Nonetheless, the differences in regression lines found by Lee and Smith have important implications for school policy. Although the effect of PCR on the relationship between socioeconomic status and gain in mathematics achievement does not appear large in Figure 2 (defined for the same dimensions as the variable slopes in Figure 1), note that the predicted difference in gain in mathematics achievement between a student of moderately low socioeconomic status and a student of moderately high socioeconomic status in schools engaged in PCT would be .76, nearly three fourths of a standard deviation, while it would be only .32, about a third of a standard deviation, in PCR schools (these effects were again estimated while controlling for many of the most important alternative explanations for achievement gains). In a school engaged in PCT we expect a student of moderately high socioeconomic status to gain about three fourths more of a standard deviation in mathematics achievement during the first two years of high school than her schoolmate who is of moderately low socioeconomic status. In a school engaged in PCR we would expect this difference to be reduced by 50%, to about a third of a standard deviation. Furthermore, the effects of PCR schools just reported are in comparison with schools engaged in other, more traditional reforms. The effects of PCR on gain in mathematics achievement and on the relationship between socioeconomic status and gain in mathematics achievement would be approximately 50% stronger if comparisons were made with schools that engaged in no reform practices at all (as given in Lee & Smith, Table 6). By using multilevel models, Lee and Smith have demonstrated that the social context defined by a school’s organization affects students’ learning, as well as the relationship between the student’s social context (in this case, measured as his or her socioeconomic status) and learning.

Multilevel models are now being broadly used to specify and estimate effects of schools on students (e.g., Gamoran, 1996; Lee & Bryk, 1989; Lee & Smith, 1993, 1996; Lee et al., 1997; Portes & MacLeod, 1996), parents (Kerbow & Bernhardt, 1993), and teachers (Bidwell et al., 1997; Lee & Smith, 1991). Many of these models become quite sophisticated at disentangling complex effects. For example, consider a two-level model of factors predicting teachers’ orientations to teaching within schools (Bidwell et al., 1997). Critical among the teacher-level predictors is the teacher’s subject field. As Grossman and Stodolosky (1995) demonstrated and Bidwell et al. confirmed, mathematics teachers place significantly less stress on a progressivist teaching style (e.g., engaging students in questions and answers, encouraging students to explore their own ideas) than teachers in other fields. Methodologically, the effects of subject fields were treated as fixed in Bidwell et al. by entering a series of dummy variables at the teacher level of a multilevel model. Thus, these dummy variables represent institutionalized aspects of teaching associated with teaching fields. At the second level, the model contained organizational characteristics of schools as well as random effects of schools. Multilevel models have been used to estimate effects of other institutions such as state testing practices (Schiller & Muller, 1997) and tracking (Lee & Bryk, 1989; Pallas et al., 1994). Thus, a basic two-level model can be used to explore institutional and organizational effects.
FIGURE 2
Mathematics Gains by Socioeconomic Status Averages Across Schools

Standardized Socioeconomic Status

- -- POR Schools
- ----- Traditional Reform Schools

\[ .16 = \hat{\gamma}_{10} + \hat{\gamma}_{11} \]
\[ .38 = \hat{\gamma}_{10} \]
\[ 4.76 = \hat{\gamma}_{00} \]
\[ .86 = \hat{\gamma}_{01} \]
Because teachers teach more than one class, the preceding analysis by Bidwell et al. (1997) could be extended to three levels of classes within teachers within schools. For example, Raudenbush, Rowan, and Cheong (1993) found that as much as 64% of the variation in teaching approaches was that between classes within mathematics teachers, although the percentage of variation within teachers differed depending on subject area (science: 39%; English: 51%; social studies: 24%). In general, teachers modify their specific goals (as measured by Raudenbush et al.) from class to class more than their general orientations to teaching (as measured by Bidwell et al.), suggesting that teachers may have a general teaching style but that they adapt their approach according to the curricular track of a class, grade level, and so forth.

Three-level models also can be used to assess changes in achievement over several time periods (Level 1) as a function of student characteristics (Level 2) and school characteristics (Level 3) (see Bryk & Raudenbush, 1992, chap. 8, for a general discussion). For example, Raudenbush and Bryk (1988) extended the analysis of growth in terms of difference scores (such as in the example of Lee and Smith) to one of linear growth over several time periods. They found that about 82% of the variation in growth in mathematics achievement was between schools, as opposed to 18% within schools! This finding suggests that we need to do more to explore the causes of variation in mathematics achievement growth at the student and school levels, with potentially important policy implications.

Two-level multilevel models have also been extended to incorporate multiple sources of random effects (Rasbash & Goldstein, 1994; Raudenbush, 1993). For example, Raudenbush (1993) developed a multilevel model including random effects of the schools students attended and the neighborhoods from which they came. Thus, the models include two important cross classifications that define students’ social contexts. Because neighborhoods are not nested within schools (students from the same neighborhood may attend different schools), typical two- or three-level models do not apply. The key to Raudenbush’s solution is to include dummy variables representing schools in Level 1 of a multilevel model of students nested within neighborhoods. But the number of schools could potentially be large, taxing the degrees of freedom for estimating the effect associated with each dummy variable. Building on Lindley and Smith (1972), Raudenbush’s approach was to consider the effects of the schools represented by the dummy variables as “exchangeable” (i.e., drawn from a common distribution). Raudenbush found that twice as much variance in student attainment could be attributed to neighborhoods as schools, thus addressing an important issue for those attempting to define the relevant social contexts for students. Raudenbush and his colleagues have followed up on this finding by exploring the effects of neighborhoods on deviant behavior (Sampson, Raudenbush & Earls, 1997).

Recent advances in the specification of the Level 1 model have allowed researchers to address how social contexts affect dichotomous outcomes such as dropout (Bryk & Thum, 1989; Rumberger, 1995) and deviant behavior (Sampson et al., 1997). These outcomes are particularly sensitive to social contexts because they represent forms of detachment from social institutions. Models with dichoto-
mous outcomes pose special problems for maximum likelihood estimation because the likelihood based on a logit model at Level 1 cannot be directly integrated. This has been addressed either by approximating the likelihood through a second-order Taylor expansion, known as the penalized quasi-likelihood (Breslow & Clayton, 1993; Goldstein, 1991; Longford, 1993; Raudenbush, 1995), or a more extensive Laplace approximation (Yang, 1998), or by using quadrature of the Gauss-Hermite type to approximate integration over the distribution of random effects (Hedeker & Gibbons, 1996). While quadrature is theoretically appealing, it is difficult to extend to cases with multidimensional random effects (such as in considering regression coefficients as random), and it may produce less stable estimates in cases of extremely infrequent outcomes (Yosef, 1997).

Developments to incorporate multivariate outcomes in the Level 1 model also have particular application to the study of social contexts. In the illustration of his technique, Thum (1997) found that the more a school supports professional community, the more teachers spend time on the correlated behaviors of teaching activities and school governance. The multivariate approach allows one to estimate the correlation among outcomes while addressing the potential compromise of Type I error rates.

Although multilevel models have helped facilitate many important advances in our understanding of the social contexts of schools, students, and the interaction of the two levels, many of the applications of multilevel modeling have shown that the intraclass correlations (the proportion of variance between schools) are often between 10% and 33% for various measures of student achievement in various cultures (e.g., Bryk & Raudenbush, 1992; Fitz-Gibbon, 1991; Lockheed & Longford, 1991; Plewis, 1991; Raudenbush & Bryk, 1988; Zuzovsky & Aitkin, 1991). Furthermore, the intraclass correlations for measures of teachers' attitudes or orientations range as low as 10% (Bidwell et al., 1997; Lee, Dedrick, & Smith, 1991; Rowan, Raudenbush, & Kang, 1991). Clearly, there is a considerable amount of variation among people within schools.

We might consider this variation to be a function of individual characteristics; if this explained most of the phenomena, however, then we would expect the proportion of variation within schools to be reduced considerably once we controlled for the likely characteristics of individuals related to the outcome. But typically only 10%–30% of the variance in achievement is explained at the student level (e.g., Bryk & Raudenbush, 1992; Fitz-Gibbon, 1991; Jacobsen, 1991; Lockheed & Longford, 1991; Pallas et al., 1994; Patterson, 1991; Raudenbush & Bryk, 1988; Zuzovsky & Aitkin, 1991). Even when controlling for a pretest (begging the question somewhat of earlier school effects), the variance explained at the student level goes up to 50%–60% (Pallas et al., 1994; Plewis, 1991). While impressive, this still leaves a considerable portion of variation unexplained even after controlling for characteristics such as race, socioeconomic status, gender, course taking, track placement, parental support, and other characteristics theoretically related to achievement. The situation for teachers in schools is no better, with only 10%–20% of the variation in teacher outcomes within schools accounted for (Bidwell et al., 1997; Lee & Smith, 1991; Rowan et al., 1991), even after control for the seniority of the teacher, the teacher’s subject field, and so forth. Thus, what we
know from multilevel models is that there is considerable variation among individuals within schools and much of that variation is unexplained solely in terms of the attributes of the individuals.

A place to look in accounting for further variance is in the relations among individuals within schools. Although multilevel models can incorporate characteristics ascribed to individuals or to schools as organizations, they have rarely been used to incorporate aspects of the relations among individuals that define the social contexts in which individuals work and learn. The best that multilevel models typically have done is to incorporate measures of school culture based on the aggregate perceptions of a sample of teachers that do not capture variation in individual contexts (e.g., Bryk & Driscoll, 1988) or to include measures based on individual perceptions of the global school culture that do not directly measure relations among people. Of course, the limitations just outlined would apply to any analysis of attributes of a sample of individuals that does not include relations among individuals (Coleman, 1958).

In order to move past these limitations, we must study relations among students and teachers in schools. Furthermore, if we are to refine our understandings of school processes, we cannot confine ourselves to samples of individuals in schools. We must, in at least a few schools, obtain information on all people and their relations within the school in order to capture the dynamic processes within schools. This will help us to answer questions regarding the organizational functioning of schools. For example, if a school has challenged institutionalized aspects of schooling, who generates the impetus for change, and through what channels do they persuade others to accept and adopt the change? On the student level, if a student’s social context affects his or her educational aspirations, how do students determine the friendships that define social context?

While the call to study relations among people in a school may sound ambitious, it is consistent with the goal of many qualitative studies of schools. Qualitative researchers in general (Grant, 1988; Johnson, 1990; Lightfoot, 1983; Metz, 1983; Rosenholtz, 1989), and ethnographers in particular (e.g., Mehan et al., 1986; Staessens, 1993), have taken on the challenge of describing the processes through which social contexts are established and influence decisions and behaviors. For example, Mehan et al. demonstrated how a school psychologist directed the process of a committee to determine the special education placement of a student. In this case, the decision and process were quite consistent with institutionalized aspects of special education, including the tools used to assess the student, the types of educational settings considered, and the authority of the psychologist.

But typical analyses of qualitative data address only a small portion of the relations among people in a school. For example, Mehan et al. focus on relations between committee members and during committee meetings, and only small sets of relations such as those defining cliques are addressed in the work of Grant (1988), Cusick (1983), and Metz (1983). Even relations among a small set of people, however, are affected by the more general social context. In the case of decisions regarding special education described by Mehan et al. (1986), would the committee’s process be the same if the entire faculty and staff were polarized with
regard to how to educate students with disabilities? How does the size of the faculty affect the process of a single committee? Is there a need to coordinate practices with others in the school?

Some anthropologists and sociologists have argued that, in order to understand the context of a single relation, one must examine and characterize the entire network of interpersonal relations (Granovetter, 1973; Mitchell, 1973; Newcomb, 1950; Parsons & Shils, 1954; Simmel, 1955). Micro processes cannot be understood unless they are related to the macro structure (Collins, 1981). For example, when teachers share information or exchange opinions, are they more able to influence one another if they are members of a common professional circle than if they operate in relatively segregated regions of a school? An answer to this question would help reveal how the social context of the school affects the experiences and actions of faculty, staff, and administrators. Therefore, the contribution of ethnography can be augmented by establishing the complete context of relations, the social network, in a school. The techniques for doing so are the subject of the next section.

EFFECTS OF SOCIAL CONTEXTS WITHIN SCHOOLS: METHODS AND MODELS IN SOCIAL NETWORK ANALYSIS

There is a deep history of analyses of the set of relations among people in schools. In fact, some of Moreno’s (1934) first sociograms graphically represented the sets of relations among students in a training school. Much of the earlier work linked characteristics of students’ personalities with their relative social standing (Blyth, 1958, 1960; Bonney, 1943; Boyd, 1965; Cook, 1945; Evans, 1962; French & Mensh, 1948; Gerber, 1977; Gronlund, 1950, 1959; Jennings, 1943; Northway, 1954; Olson, 1949; Powell, 1948; Zeleny, 1941), and then researchers turned to analyses of small group processes within the classroom (Flecker, 1967; King, 1960; Newcomb, 1961; Pratt, 1960; Schmuck & Schmuck, 1975). Important work in secondary schools has linked patterns of social structure to the organization of classrooms (Bossert, 1979; Epstein & Karweit, 1983; Flanders & Havumaki, 1960; Hallinan, 1976; Schmuck & Schmuck, 1975). For example, Epstein (1983, ch. 5) found when students participated in classroom decision making, distancing the classroom processes from the full guidance of the teacher, the students were more likely to develop diverse and extensive social ties. Similarly, Sheare (1978) demonstrated that modification of classroom structure can increase the low social standing experienced by students with disabilities. This low social standing may be experienced even by those who are physically mainstreamed into a regular education classroom (Bruiniks, 1978a, 1978b; Bryan, 1974; Siperstein et al., 1978), and is thus a critical issue for fully integrating students with disabilities.

Although many of these studies explored relations among students, they did not address the set of relations in a classroom as a system. Correspondingly, although their interest in social relations suggests a movement toward consideration of individuals’ interdependencies, typically their analyses treat individuals as independent. As we move toward analyses of the entire set of relations among individuals that define the system of a classroom or school, we turn to quantitative methods used by social network analysts.
Many of the methods developed for social network analyses can be applied to analyses of the relations or interactions among the people in a school (see Scott, 1991, for an introduction to social network analysis; see Wasserman & Faust, 1994, for an encyclopedic review of social network methods; and see Wasserman & Galaskiewicz, 1994, for recent advances in social network analysis). In particular, in the following subsections, I review the techniques most relevant for the study of the social context of schooling. These techniques include graphical representation of sets of relations among people, identification of groups or subgroups of people based on the pattern of relations, modeling of attributes of people as a function of relations in the social network (influence), and modeling of the pattern of relations in a social network as a function of attributes of people (selection).

**Graphical Representations of Social Context**

Coleman’s (1961) *Adolescent Society* featured the construction of one of the earliest sociograms of relationships among students in a school. Through his sociograms and related analyses, Coleman demonstrated the presence of cliques of students (jocks, academic elites, etc.) that reflected emphases and actions of the faculty and of the local community, findings that were subsequently supported by Eckert (1989). The graphical representation of relationships among the students generated by Coleman (1961) and shown in Figure 3 helped to reveal how the students functioned in the social context they constructed. On one hand, the representation reveals the basic dimensions along which cliques formed. These cliques gained their salience through positive and negative sanctions of the faculty, reflecting differences in the faculty’s experiences as well as values in the community. On the other hand, the graphical representation defines the context of each individual that may or may not be totally subsumed by the student’s clique membership. Thus, there are some individuals who are central to a specific clique, others who span different cliques, and others who are isolated. Sociograms such as Coleman’s provide an overview of social structure through which qualitative and ethnographic accounts of specific relations can be integrated.

There have been several extensions of the basic sociogram that can be applied to representing the multiple social contexts of individuals in schools. One of the fundamental problems of the original sociograms such as Coleman’s was that people were located in the two dimensions arbitrarily, based on the aesthetic of the researcher (the choice to use only two dimensions is also arbitrary, although typically necessary for effective graphical representation). In an advancement, multidimensional scaling (MDS) techniques have been used to determine the location of each actor (cf. Krackhardt, Blyth, & McGrath, 1994) in a small number of dimensions. Furthermore, although MDS techniques can be applied to large data sets, their application does not always result in a helpful reduction of the data. Lost is Coleman’s intuitive appreciation for the importance of cliques, or subgroups, among people in a school. Inevitably, researchers who seek to interpret MDS-based sociograms draw theoretical or graphical circles around subsets of people so that they may interpret the image (e.g., Kadushin, 1995; Laumann, 1970; Nakao & Romney, 1993). But these circles are typically based on ad hoc criteria and
FIGURE 3
Early Sociogram of Friendships Among High School Students


aesthetics of the researcher and cannot be defined in terms of a formal criterion for subgroup membership.

Theoretically, it is sensible to consider organizations as composed of a set of
integrated cohesive subgroups. Cohesive subgroups were initially defined as those that had extensive capacity to attract and retain subgroup members (see Cartwright, 1968, and Mudrack, 1989, for reviews). From Moreno’s (1934) initiation of sociometric study to Homans’s (1950) and Blau’s (1977) theoretical statements and Freeman’s (1992) return, cohesive subgroups have been hypothesized as a crucial link between individuals and organizations. Not surprisingly, one of the strongest and most consistent theoretical images of the structure of organizations and systems is that of relations concentrated within, but not confined to, cohesive subgroups (Blau, 1977; Durkheim, 1933; Homans, 1950; Roethlisberger & Dickson, 1941; Simon, 1965). This conception is also consistent with theories defined at the level of the individual, in which people influence each other through direct relations within their subgroups and then integrate into the larger organization through relations spanning subgroup boundaries (Granovetter, 1973; Nadel, 1957).

Typically, studies of schools have relied on the formal organization in the form of departmental affiliations as a basis for defining cohesive subgroups (e.g., Johnson, 1990; Siskin, 1991). Through dense patterns of relations within departments, teachers may share a language for describing their work, orientations to teaching, mechanisms for decision making, and so forth (Johnson, 1990; Siskin, 1991). But the formal organization is not always most salient for people as the informal organization can have substantial effect on organizational processes (Burawoy, 1979; Coleman, 1958; Durkheim, 1984; Etzioni, 1961; Homans, 1950; Roethlisberger & Dickson, 1941; Selznick, 1961; Weber, 1958). In the case of schools, departments may become less salient in small schools when departments contain only a few teachers, in Catholic schools that have less of a departmental organization (partly because teachers with less training in specific subject fields are more likely to cross subject areas in their teaching) (Bryk & Frank, 1991), and even in large public schools, where there are often divisions within departments based on cohort, gender, or subfield (Metz, 1990). Indeed, part of the movement for restructuring schools calls for a reduction in departmentalization (Bryk, Lee, & Smith, 1990; Carnegie Council on Adolescent Development, 1989). Therefore, what is needed is a technique for identifying cohesive subgroups based on the pattern of relations among people instead of boundaries defined by the formal organization of the school.

In order to move beyond categories of the formal organization, methodologists have developed and used various techniques for identifying cohesive subgroups from data indicating relations among actors (e.g., Alba, 1973; Arabie & Hubert, 1990; Bock & Hussein, 1948; Borgatti, Everett, & Shirey, 1990; Cartwright & Harary, 1956; Davis, 1977; Everett, 1983; Freeman, 1992; Hubbell, 1965; Katz, 1947; Matula, 1972; Mokken, 1979; Phillips & Conviser, 1972; Reitz, 1988; Seidman & Foster, 1978). Many of the techniques involve graph-theoretic criteria (see Wasserman & Faust, 1994, for a review). First, the optimally cohesive subgroup is a clique in which all subgroup members engage in direct relations with each other. But such a definition is restrictive and “stingy” (Alba, 1973). Therefore, various efforts have been made to relax this criterion. An early approach required that each actor in a subgroup be able to reach all others in the subgroup
in a minimum number of steps (Alba, 1973; Luce, 1950; Mokken, 1979). For example, the relation 1→2→3 indicates a path of two steps (or length two) connecting Actor 1 to Actor 3. A criterion could be specified such that subgroup members are all connected via paths of length one or two. This criterion can be further restricted by requiring that the connecting paths occur within the subgroup (Alba, 1973; Mokken, 1979). But if influence occurs through direct relations, then it may be more sensible to define cohesive subgroups in terms of direct relations rather than overall path lengths, which may be too long to transmit much influence (Burt, 1988; Hubbell, 1965). Furthermore, the definitions based on path length are restrictive in that they specify the nature of the relationship between each pair of actors within a subgroup instead of a general relationship between each actor and all others in the subgroup.

In response to the preceding concerns, Seidman and Foster (1978) and Seidman (1983) introduced definitions of subgroups based on the minimum number of relations that each actor must share with others in the subgroup or based on the maximal number of relations that can be absent between each actor and subgroup members. But the issue arises as to how to choose the minimum or maximum, and often these choices depend on post hoc interpretations of subgroup membership in terms of other characteristics of the actors. Furthermore, the application of Seidman and Foster’s approach (as well as Borgatti et al.’s, 1990, extension) often results in the identification of several overlapping small clusters that are difficult to interpret (Frank, 1993; Freeman, 1992; Kadushin, 1995). Such overlapping clusters are inconsistent with many of the theoretical characterizations of systems composed of nonoverlapping subgroups. In particular, overlapping boundaries fail to establish “an inside and an outside” (Abbott, 1996, p. 872) necessary to define a sociological entity. How can we differentiate processes within subgroups from those between subgroups if two actors can simultaneously be members of the same subgroup and members of different subgroups?

Perhaps the most promising approaches for identifying nonoverlapping cohesive subgroups are those that involve goodness of fit, or statistical, criteria associated with the fitting of subgroups to social network data (e.g., Alba, 1973; Bock & Husain, 1950; Freeman, 1992; Seidman, 1983). In each case, one can conceptualize a model in which membership in the same subgroup (vs. membership in different subgroups) is used to predict whether two actors are related. The criteria measuring the fit of such models then define cohesiveness in terms of a concentration of relations within subgroups relative to the extent of relations between subgroups. These statistical measures have the advantage of allowing for relations within and across subgroup boundaries at rates that are defined relative to the data instead of absolute criteria. Thus, they accommodate variation in the data not by forcing the identification of overlapping subgroup boundaries based on fixed criteria but by allowing the identification of nonoverlapping, but permeable, subgroup boundaries.

In a recent example of the use of stochastic criteria, I defined cohesiveness in terms of the odds ratio (AD/BC) in Table 1, representing the association between membership in the same subgroup and the occurrence of relations (Frank, 1995a).
The odds ratio of Table 1 is large to the extent that actors engage in relations with members of their subgroups (Cell D) and do not engage in relations with members of other subgroups (Cell A). The odds ratio is small to the extent that actors do not engage in relations with members of their subgroups (Cell C) and actors engage in relations with others who are not in their subgroup (Cell B). Because the odds ratio is stochastic, with values on the diagonals of Table 1 essentially evaluated relative to the marginals, it accommodates variation in subgroup sizes and actors' propensities for engaging in relations (see Frank, 1995a, pp. 33–34, for a discussion).

A clustering algorithm can be used to identify nonoverlapping but permeable subgroup boundaries by assigning actors to subgroups so as to maximize the odds ratio of Table 1 (Frank, 1995a, 1996; software will be incorporated into the next release of the general social networks software package UCINET [Borgatti, Everett, & Freeman, 1992]). The representation of relations nested within cohesive subgroups then helps to establish the social contexts for individual actors, and, because the boundaries are commonly defined across all actors and do not overlap, they can also be used to characterize meaningful divisions in the pattern of relations that might affect organizational function. For example, the subgroup boundaries might reveal factions among teachers associated with differences in discipline policy, approaches to teaching, union support, and so forth.

In a recent article, I (Frank, 1996) applied my algorithm to represent the structure of professional discussions among teachers in a single school. This representation allowed me to link the pattern of professional discussions to the teachers' race and gender, as well as their orientations to teaching. I identified cohesive subgroups of teachers based on their indications of the professional discussions in which they engaged (professional discussions were measured on the basis of self-reports of teachers, who indicated the five others with whom they engaged in professional discussions most frequently and then ranked the extent of professional discussion on a scale ranging from once a month [1] to daily [4]). I then embedded the subgroup boundaries into the sociogram in Figure 4 by applying

---

**TABLE 1**

Assocation Between Common Subgroup Membership and the Realization of a Relation Between Actors

<table>
<thead>
<tr>
<th>Subgroup Membership</th>
<th>Relation Realized</th>
<th>No</th>
<th>Yes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Different</td>
<td></td>
<td>A</td>
<td>B</td>
</tr>
<tr>
<td>Same</td>
<td></td>
<td>C</td>
<td>D</td>
</tr>
<tr>
<td></td>
<td>Unrealized</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Realized</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Total possible</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

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FIGURE 4
Professional Discussions Among Teachers in “Our Hamilton High”

Solid lines within subgroups, dotted lines between, thickness = frequency.
Scale = 4/(density of discussion)

MDS within and between subgroups (see Frank, 1996, for the technical details of this procedure). The result is a method for constructing sociograms that is consistent with Coleman’s intuitive representation but applies empirically based techniques for defining subgroup membership and for representing the actors and their relations in two dimensions.7
Figure 4 establishes a basis for integrating qualitative data and information from survey instruments to characterize the processes through which teachers are affected by their social contexts. As indicated in school documents, the student population at “Our Hamilton High” has become increasingly disadvantaged over the years as poor families have moved to the district from a nearby city and as the children of the more established wealthier families have aged. The teachers have responded in various ways to this exogenous change. Some who had difficulty adapting to the change sought early retirement. Others altered their mode of relating to the students, befriending the students whom they felt were most in need. In this sense, the school is similar to others described by Grant (1988) and Metz (1990). A core of teachers relate to the new types of students by acting as “moral agents,” inculcating students into a specific set of values emphasizing citizenship and responsibility by keeping firm control of the classroom and through personal example (see Bidwell et al., 1997, for a definition and operationalization of moral agency in terms of responses to survey items [reliability = .74]).

By assigning the teachers identification numbers in the sociogram to represent their emphasis on moral agency (the lower the number, the higher the rank on moral agency), I used the image in Figure 4 as a basis for inferring processes through which teachers influenced one another (Frank, 1996). To begin, moral agency is cultivated within Subgroup A as the members of that subgroup engage in discussions with one another on a near daily basis (as indicated by the thick lines within the boundary of Subgroup A and as observed during fieldwork). Once a week or once a month, one of the teachers in Subgroup A engages in discussions with a teacher outside the subgroup (as indicated by the thinner lines between members of Subgroup A and members of other subgroups), thus possibly influencing the member of the other subgroup. The effect of these discussions is critical to integrating the subgroups into the totality of the organization, as opinions, information, and so forth that accumulate in each subgroup during daily discussions are transmitted to the other subgroup. Therefore, even teachers who do not adopt moral agency in direct response to changes in the student population may be affected, through direct and indirect discussions, by the orientations of the teachers in Subgroup A.

Although others have observed the processes through which teachers socialize one another on a dyadic level (Fuller & Izu, 1986; Grant, 1988; Hanson, 1978; Lightfoot, 1983; Metz, 1990; Rosenholtz & Simpson, 1990), Figure 4 represents the structure through which the socialization process occurs at the level of the school. Therefore, I was able to describe moral agency as being cultivated within Subgroup A and then spreading to other subgroups, where it encounters competing orientations. Of course, this process could be described with an alternative orientation being cultivated in another subgroup and then moving to the members of Subgroup A. Indeed, the image in Figure 4 suggests an equilibrium of the system, with those in Subgroup C who are mixed and moderate in their orientations mediating between the competing orientations of those at the top and bottom. Thus, the image in Figure 4 represents how processes within one subgroup may generate aspects of the organizational culture that then affect all people in the school.
Images similar to Figure 4 also could be used to explore the process through which institutions penetrate the school as an organization. Who is responsible for implementing any given institution in a school, and how did they persuade others that this was a valuable practice to implement? For example, who is responsible for defining the possibilities for special education, and how did they influence others to adopt the same mind-set? One can trace such processes in images (such as in Figure 4) that combine information regarding individuals’ attitudes or orientations with a helpful reduction in the representation of relations among people. Of course, images such as that in Figure 4 also have the potential to represent the relational structure through which people in schools challenge prevailing institutions, opening the possibility for studying the processes of school reform.

Graphical representations and clustering algorithms drawn from social network analysis have also been used to represent the structure of relations among students. For example, Friedkin and Thomas (1997) refined the definition of tracks and levels in high schools by analyzing the structure constructed through course-taking patterns, and Quiroz, Gonzalez, and Frank (1996) represented connections established through students’ participation in extracurricular activities. Furthermore, these techniques could be used to extend earlier analyses of the friendship networks of students (Epstein, 1983; Hallinan, 1976). For example, although we may know the tendencies of students to choose others of similar gender or of higher socioeconomic status, it is helpful to know the pattern of friendship choices in classrooms that fully defines the social context in which each student learns.

Although graphical representations of the social structures within schools offer considerable potential as an aid to understanding the processes through which social contexts are defined, they do not provide a quantitative summary or formal model of the relationship between social structure and other attributes of people. To what extent do teachers influence each other’s orientations? To what extent do students with similar aspirations choose to become friends? It is to these types of questions that I turn in the following subsections.

**Models of Effects Mediated by the Social Context**

(Influence Models)

The quantitative methods for analyzing social networks go beyond the graphical representation of the structure of a social network. In particular, models of social network processes can represent the effects of interpersonal influence that emerge out of a social context. For example, we might ask to what extent teachers’ attitudes toward educating students with disabilities are influenced by the attitudes of other teachers and staff in their school. This question reflects a fundamental component of the process that ultimately affects the schooling experiences of students with disabilities (Triandis et al., 1984; Watts, 1984), which in turn is one of the most important factors in determining how teachers interact with students with disabilities (Fuchs et al., 1995; Jones & Guskin, 1984; Triadis et al., 1984).

In order to write the basic model of influence through interpersonal relations, define $w_{ij}$ to indicate the extent or existence of a relation between individuals $i$ and $j$, as perceived by $i$. Define $y_i$ to represent an attribute (an opinion, belief, or orientation) of person $i$ that
might be influenced through relations with others. A model for \( n \) people representing the influence of others on \( y_i \) through interpersonal relations can be defined as

\[
y_i = \rho \left[ \sum_{\ell=1, \ell' \neq i}^{n} w_{ii'} y_{i'} \right] + e_i,
\]

where \( \rho \) represents the extent of the network effect associated with \( \sum_{\ell} w_{ii'} y_{i'} \), the sum of the attributes of others to whom an actor is related. As in the case of a general linear model or the Level 1 model of a multilevel mode, the errors are assumed to be independent and identically distributed and normal, with mean zero and variance \( \sigma^2 \).

One possible interpretation for \( \rho \) is that it indicates the effect of alters \( (i') \) on ego \( (i) \) through the social network (Bovasso, 1996; Burt, 1987). This might occur through the process of cohesion, in which people influence one another by sharing information or persuasion (Barnes, 1972; Blau, 1977; Bott, 1971; Collins, 1981; Festinger, 1950; Homans, 1950; Mitchell, 1973), or through structural equivalence, where the \( w_{ii'} \) indicate the role that people occupy and the \( y_{i'} \) represent a behavior that is a function of the behaviors of others who occupy similar roles (Burt, 1987; Merton, 1957; Nadel, 1957; Radcliffe-Brown, 1940). For example, cohesion applies when students’ educational decisions and aspirations are influenced through direct discussions (Davies & Kandel, 1981; Duncan, Haller, & Portes, 1968; Epstein, 1983; Hartup, 1978; Sewell, Haller, & Ohlendorf, 1970). On the other hand, students who occupy similar positions defined by curricular tracks may develop similar educational aspirations (Bowles & Gintis, 1976; Hansell & Karweit, 1983). This may be in part to achieve balance (Cartwright & Harary, 1956; Heider, 1958; Newcomb, 1961) between their aspirations and interpersonal relations.

Recently, Leenders (1995) emphasized that \( \rho \) is not necessarily interpreted as the effect of others through interpersonal relations, because we do not know from cross-sectional data whether individuals’ attributes changed as a result of the pattern of relation (influence) or whether the pattern of relation changed as a result of the attributes (selection). Similarly, Marsden and Friedkin (1994, p. 13) claim only that the direct effect of one person’s response to the others through the social network is “consistent” with the presence of an influence process. Thus, Leenders describes \( \rho \) as “descriptive” or as a governing factor but not necessarily as indicative of influence of actors on one another. In this sense, interpretations of analyses of cross-sectional social network data are subject to the same constraints as analyses of other cross-sectional data (Cook & Campbell, 1979). But even if \( \rho \) is only “descriptive,” it has the potential to represent an important characteristic of an organization: the alignment of the pattern of relations and the distribution of an attitude, behavior, or orientation (Xu, 1997).

Regardless of the interpretation of \( \rho \), the unique characteristics of the dependencies in observations in social network data present challenges in the estimation
of parameters such as $p$. If we define $y$ as an $n \times 1$ vector of attributes, $W$ as an $n \times n$ matrix representing relations, and $e$ as an $n \times 1$ vector of error terms, $e$, we can rewrite Equation 2 in matrix form:

$$y = pWy + e$$

(3)

For example, we might write

$$\text{Attitude toward inclusion practices} = p (\text{Professional discussions}) \times (\text{Others' attitudes toward inclusion practices}) + e,$$

(4)

and observe the fundamental limitation in estimation of the parameter $p$: The vector $y$ (attitude toward inclusion practices) appears on both sides of the equation. The result is that ordinary least squares estimates of $p$ are biased (Anselin, 1988; Ord, 1975). In response, Ord described a procedure for obtaining maximum likelihood estimates of $p$ that is generally available (Friedkin, 1990), although there is still work being conducted on the technical details (Dow & Leenders, 1997; Duke, 1993; Frank & Xu, 1997).

Models such as Equation 2 also can be specified and estimated for longitudinal data, estimating changes in individuals’ beliefs or orientations as a function of the beliefs of the others with whom they engaged in relations in previous time periods (Friedkin & Marsden, 1994, argue that ordinary least squares estimates are unbiased for such longitudinal models). For example, Epstein (1983) found that students’ self-reliance and achievement were influenced by the self-reliance and achievement of their peers at a previous time point. Friedkin (1997) and Friedkin and Johnson (1990) also developed models of the processes through which people influence one another as they move over several time points from an initial set of beliefs to a final state in which there is equilibrium between beliefs and the pattern of interaction.

Equation 2, as well as longitudinal versions of this model, can also be easily modified to incorporate other attributes of people. For example, using the data from Coleman (1961), Duke (1993) found that inclusion of peer academic performance increased the $R^2$ from .35 (for a model including gender, mental ability, and socioeconomic status) to .44 in predicting students’ academic performance. Furthermore, one can include effects through multiple networks (e.g., through general discussions or lunchroom conversations) in the cross-sectional (Doreian, 1989) or longitudinal case. Therefore, models of network effects or influence can help us to identify the extent to which a set of people such as teachers or students change each other’s beliefs through interaction or friendship. But the price is not cheap in terms of data collection. At a minimum, a limited version of a network effects model can be estimated by knowing the beliefs of a sample of people (egos) and the beliefs of each of the others (alters) with whom they acknowledged engaging in interactions or friendship (e.g., Epstein, 1983). Ideally, one would obtain data on all people in a given network.

**Models of the Construction of Social Context (Selection Models)**

Although models such as in Equation 2 represent a largely untapped potential for representing and estimating the effects through which people in a school in-
fluence one another, the pattern of relations among the people was considered fixed over time. But the recent awareness of how teachers in a school construct their patterns of relation (Bird & Little, 1986; Darling-Hammond & McLaughlin, 1995; Little, 1993) calls for processes captured by a second set of models for analyzing social networks. For example, if we define professional discussions to either occur or not occur between individuals $i$ and $i'$ over the interval $t-h \rightarrow t$, as represented by $w_{ii'}^{t-h \rightarrow t}$, we can present the following logit model for $w_{ii'}^{t-h \rightarrow t}$:

$$\log \left( \frac{p[w_{ii'}^{t-h \rightarrow t} = 1]}{1 - p[w_{ii'}^{t-h \rightarrow t} = 1]} \right) = \theta_0 - \theta_j y_{ij}^{t-h} - y_{ij'}^{t-h}. \quad (5)$$

The left-hand side of this equation transforms, via the logit, an expression for the probability that $w_{ii'} = 1$ to the line of real numbers (Agresti, 1984). Here $\theta_0$ represents an intercept and $\theta_j$ represents the homophily effect (Blau, 1977; Feld, 1981; Festinger, Schachter, & Back, 1950; Homans, 1950), whereby people choose to engage in relations with others with similar attributes (as captured by $y_{ij}^{t-h}$). For example, we might explore the tendency for teachers to engage in professional discussions with others of similar orientations or for students to be friendly with others of the same gender.

Again, the dependencies inherent in social network data pose interesting challenges for estimation. In obtaining estimates of the parameters in Equation 5, one’s first inclination might be to use maximum likelihood techniques such as those available to estimate the parameters in logit models (e.g., Agresti, 1984). But it is difficult to define the likelihood of the parameters as a function of the data in Equation 5, because the observations are not independent. To begin, the relation between $i$ and $i'$ is not independent of the relation between $i'$ and $i$. Such dependencies are accounted for in earlier $P_1$ models of selection (Fienberg, Meyer, & Wasserman, 1985; Fienberg & Wasserman, 1981; Holland & Leinhardt, 1981; software are available in the general social networks package UCINET [Borgatti et al., 1992]) by specifying the set of relations among the dyad as the unit of analysis (including the relation from $i$ to $i'$, as well as the relation from $i'$ to $i$). While the $p_1$ approach represents an important advancement in the estimation of parameters such as in Equation 5, the respecification of the models does not account for dependencies among pairs outside the dyad.

But a new estimation approach, developed by Frank and Strauss (1986) and Strauss and Ikeda (1990) and described by Wasserman and Pattison (1996), shows that estimates from a logit model can be used to obtain estimates while conditioning the relation between each pair of people on the relation between every other pair of people in the network. For example, we might model whether two people are friends as a function of the number of friends they have in common, the number of friends of friends they have in common, and so forth. In a key point, Strauss and Ikeda demonstrate that one need only condition on relations among sets of up to four people in order to capture all of the dependencies in a network.

The estimation of parameters in these conditioned models is based on the maximization of the pseudo-likelihood that can be obtained via standard logit estimation procedures (such as those available in SPSS and SAS), provided one controls
for the full array of dependencies among the observations by incorporating sets of specifically defined independent variables in the model (the software for constructing these independent variables is available at the Web site http://kentucky.psych.uiuc.edu/pstar/index.html). One may also use techniques based on Hubert’s (1987) QAP procedure to obtain Monte Carlo–based p values for outcomes measured on a continuous scale.

Models such as in Equation 5 can be used to establish whether a given factor is linked to how individuals construct their social contexts. For example, several authors have found that students prefer to establish friendships with others of the same gender, although the effect is reduced with age (e.g., Epstein, 1983; Hallinan, 1976; Leenders, 1995). Furthermore, similarity on multiple characteristics may be represented in models such as in Equation 5 in order to differentiate among factors that affect how students and teachers construct their social contexts. For teachers, we could compare the effects of a formal requirement to communicate against individual preferences for engaging in professional discussions (Darling-Hammond & McLaughlin, 1995; Selznick, 1961). For students, we could compare the effect of proximities generated by curricular tracking versus affinities based on attitudes toward education.

Although models of selection can help us understand the formation of social contexts, as was the case for models of influence, the data demands of selection models are relatively high. One can specify a limited version of a selection model by knowing the attribute of each ego and each alter with whom egos indicate a relation or engaging in communication. Ideally, one would obtain information on all of the people in a network in order to capture the complete dynamic of selection and estimate the effects of various measures of dependencies.

Combining the findings of selection models with influence models, we observe how individuals define the social contexts through which they are influenced. For example, there is some evidence that high school students are especially influenced by their closest friends (Cohen, 1971). Moreover, a recent class of models has emerged that integrates influence and selection in studies of network evolution (Carley, 1990, 1991; DeVree & Dagevos, 1994; Frank, 1995b; Frank & Fahrbach, 1997; Leenders, 1995; Stokman & Zeggelink, 1996). Although in their infancy, models of network evolution have the potential to play a critical role in the understanding of the social context of schooling. Simply by focusing on model specification, we can learn how to better represent the processes through which people construct social contexts and through which they are influenced by the social contexts they construct. These models may have important policy implications in education. For example, should a professional development program target those teachers who are already most inclined to adopt the program, at the risk of making the program an issue that factionalizes the teachers, such as is described by McLaughlin and Marsh (1979)? Consideration of such an issue points to the critical importance of teachers’ social contexts in their continued learning and in the sustained function of the school (Lieberman, 1995; MacIver & Epstein, 1991; Staessens, 1993). In particular, there is increasing recognition that reforms must be holistic, addressing the processes through which teachers form relations...
with one another and influence one another as they contribute to the construction of school culture (Darling-Hammond & McLaughlin, 1995; Goodman, 1995; Lieberman, 1995; McDonald, Smith, Turner, Finney, & Barton, 1993; Staessens, 1993; Weiss, 1995).

A General Framework of Social Contexts in Schools

The sets of models including social network processes as predictors and outcomes represent pieces of the general framework of the social processes in schools presented in Figure 5. Building on generic models such as those included in Erbring and Young (1979) and Friedkin and Johnson (1990), the figure represents the mechanisms through which two sets of people in the school, faculty (and administrators) and students, engage in relations and influence each others' attitudes and behaviors. At the top left, faculty relations and background characteristics of teachers combine with the effects of external influences (these can include exogenous policy constraints such as legal mandates and the organization of district governance) to affect teacher characteristics such as orientation to teaching and beliefs. Relating these effects back to Equation 2, the faculty relations represent the independent variable $\Sigma f W_{ij} Y_i$, and the external influences are associated with the error terms $e_i$ (note that the effect of background characteristics can also be included in the model). As we move across the top of the figure, teachers' characteristics then affect the relations in which they engage, corresponding to the processes specified in Equation 5, at which point the cycle of effects is reinitiated.

An isomorphic structure and the corresponding process are posited for students in the lower half of Figure 5. In the middle of Figure 5 is the focal point: interactions within and outside of the classroom between teachers and students. This focal point represents the processes through which two distinct sets of people, faculty (and administrators) and students, are media through which forces exogenous to the school confront one another. It is what makes schools unique (e.g.,
Ashton & Webb, 1986; Barnes, 1976; Bird & Little, 1986) and is the subject of considerable ethnographic research (e.g., Eder, 1982; Rist, 1970; Wilcox, 1982).

As an example, the exogenous effects on teachers may represent effects referred to as institutional (DiMaggio & Powell, 1991; Meyer & Rowan, 1991) or cultural (e.g., Apple, 1990; Mehan, 1992). For example, teachers may hold certain orientations toward teaching partly because of their training and exposure to the beliefs of others in their subject field outside of the school (Grossman & Stodolsky, 1995). Thus, these beliefs are partly institutionalized in the subject matter. Teachers’ beliefs are then expressed in the professional discussions in which they engage, a process that is guided by aspects of the organization of the particular school. Teachers’ beliefs also are expressed as classroom practices during interaction with students. The experiences of the classroom and of professional discussions with others then modify teachers’ beliefs, as the cycle continues.

Coming from the student level, students’ characteristics are formed on the basis of their interactions with others and their backgrounds (Apple, 1979; Bowles & Gintis, 1976; Eder, 1981; Gamoran, 1996; Hollingshead, 1949; Lee & Bryk, 1989; Lee & Smith, 1993). Much of the effect of background, such as that associated with socioeconomic status, can be considered an institutionalized aspect of the student’s culture. Students’ characteristics, in turn, affect the interactions with teachers within and outside of the classroom that partly define the culture of the school (e.g., Delpit, 1988; Metz, 1990). In particular, we have become increasingly aware of the challenge of classroom interaction between teachers and students who are influenced by different cultures defined within and outside of the school (e.g., Delpit, 1988). Interactions between students and teachers then affect future student relations and characteristics as the cycle is continued (e.g., Epstein, 1983). Thus, by representing social processes within schools, models of social network data capture the interplay between multiple levels of schooling (institutional, organizational, and individual) that are not completely captured by the more established multilevel models of independent individuals nested within schools.

**FUTURE RESEARCH: SOCIAL NETWORK MODELS IN MULTILEVELS**

The social network models were developed in the preceding section with respect to estimating effects in a single system. Thus, although the basic social network models of influence and selection can inform other research and establish a scaffold for qualitative research, they do not establish a sound basis for policy-making by comparing effects across multiple settings. It is here that multilevel models make their greatest contribution. Through the multilevel framework, the researcher can characterize the extent of variation in an outcome within and between schools and specify and estimate effects of individual- and school-level characteristics (including those effected through policies such as restructuring), as well as the interaction of individual and school characteristics.

There is also great potential to integrate multilevel models and models of social network processes. For example, a set of papers presented at the 1997
meeting of the American Sociological Association combined multilevel models with measures of social structure to assess the effects of social capital on educational outcomes (Carbonaro, 1997; Desimone, 1997; Epstein & Connors-Tadros, 1997; McNeal, 1997; Morgan & Sorensen, 1997). One of the keys in this area will be to refine indices of social structure such as centralization and polarization (see Freeman, 1978, or Wasserman & Faust, 1994, for discussions of existing indices). For example, Friedkin and Thomas (1997) used social network analysis to identify course-taking positions based on the hypergraph of students' transcripts. These positions then accounted for considerable variation in student achievement, even controlling for socioeconomic status, minority status, prior achievement, and at the school level, sector. In fact, their findings indicate that once controlling for curricular positions, the effects of the covariates are dramatically reduced, indicating that the schooling experience defined by course taking patterns has a strong direct effect on achievement.

The specific models of selection and influence can also be integrated into the multilevel framework. For example, consider the following multilevel model in which the effect of teachers’ influence varies randomly across schools:

At the teacher level:

\[
\text{Attitude toward inclusion}_{ij} = \beta_{0j} + \rho_j \sum_{i'; i' \neq i}^{n} \text{professional discussion}_{ij} \text{Attitude toward inclusion}_{i'j} + e_{ij}. \quad (6)
\]

At the school level:

\[
\beta_{0i} = \gamma_{00} + u_{0i}, \quad \text{and} \quad \rho_j = \gamma_{0} + u_{\rho j}.
\]

Here the extent of the network effect, as captured by \( \rho_n \), varies randomly across schools (as captured by \( u_{\rho j} \)). Although some have argued that, in general, teachers have little influence over one another (Cusick, 1983; Lortie, 1977), the extent of influence may be critical to the effective implementation of professional development and innovations (Bird & Little, 1986; Darling-Hammond & McLaughlin, 1995; Little, 1984). Therefore, it is important to understand the circumstances under which the network effect is likely to be large. For example, is there a stronger network effect when a school engages in practices consistent with restructuring that are designed to facilitate relations between teachers? If there is, might that help the school to implement other reforms?

Bidwell and Bryk (1996) are already exploring models such as Equation 6 to investigate the factors that affect teachers’ orientation to and engagement in teaching. They have expanded on this model by differentiating between effects within...
and between subgroups such as those inferred from Figure 4. On one hand, sub­
group members may have more effect than others, because there is a strong ten­
dency to conform to subgroup norms (e.g., Merton, 1957). On the other hand,
teachers from outside a subgroup may exert greater influence as a result of the
novelty of their information (this is consistent with Granovetter’s, 1973, strength-
of-weak-ties argument).

Specification of models such as in Equation 6 and estimation of the param­
eters will require further research. As already stated, the interpretation of the
typical network effect depends critically on the specification of the network
relation. The interpretation of the network effect in the multilevel model will
also depend on choices of centering. Furthermore, the Newton-Raphson al­
gorithm for obtaining maximum likelihood estimates of the parameters in mod­
els of network effects (e.g., Ord, 1975) has not been directly extended to the
multilevel framework.

The selection model (Equation 5) can also be extended to multilevels. For
example, Epstein (1983, chap. 5) found that friendships were more common
and tended to be more integrated in schools in which the students participated
in decision making. These effects would be associated with $\gamma_{01}$ and $\gamma_{11}$, re­
spectively, in the following multilevel model for occurrence of friendship be­tween students $i$ and $i'$ in school $j$ as a function of whether or not they come
from the same socioeconomic status:

At level one:

$$\log \left( \frac{p[friendship_{ii'j} = 1]}{1 - p[friendship_{ii'j} = 1]} \right) = \theta_{0j} + \theta_{1j} \text{ same socioeconomic status}_{ii'j}, \quad (7)$$

And at level two:

$$\theta_{0j} = \gamma_{00} + \gamma_{01} \text{ student participation in decision-making}_j = u_{yj},$$

$$\theta_{1j} = \gamma_{10} + \gamma_{11} \text{ student participation in decision-making}_j = u_{yj}.$$ 

The formal model defined by Equation 7 extends Epstein’s analysis by including
terms representing the random variation of the slope and intercept across schools.
We do not know, from Epstein’s analysis, how much schools vary in the overall
tendency for friendships to form, nor can we quantify how much the homophily
effect associated with socioeconomic status varies across schools. Furthermore,
dependencies among observations within the same school are captured in Equa­
tion 7, whereas they were ignored in Epstein’s analysis. Thus, models such as
Equation 7 can be used to explore the extent to which relations are segregated
according to ascriptive characteristics of either faculty or students. Understanding
the circumstances under which segregation occurs can inform reforms attempting
to reduce segregation among students or faculty.

The parameters in Equation 7 can be estimated by taking advantage of recent
advancements in the estimation of selection and multilevel models. As already
stated, maximum pseudo-likelihood estimates of the parameters in the model of
selection can be obtained by applying ordinary logistic regression procedures while controlling for dependencies among the sets of relations. Thus, it seems sensible to extend this approach through the new procedures for maximizing the marginal likelihood (Hedeker & Gibbons, 1996) or approximations to the likelihood (Breslow & Clayton, 1993; Goldstein, 1991; Raudenbush, 1995; Yang, 1998) for multilevel models with dichotomous outcomes. As was the case with models of influence, one can even incorporate effects of subgroups by specifying a relation between a pair of people to occur either within or between subgroups (see the technical appendix in Frank & Yasumoto, 1997, for a discussion of this approach).

Because the data demands are great in order to estimate the full selection or influence model, the number of Level 2 units (e.g., schools) in the extension of these models to multilevels will be limited. It will simply be difficult to obtain observations on full populations of teachers or students in hundreds of schools. Furthermore, it is quite likely that we will rely on methods that approximate the likelihood in multilevel models including influence and selection because the techniques for obtaining maximum likelihood estimates are complex or do not yet exist in the single-level case. The combination of small numbers of Level 2 units and estimates based on approximations to the likelihood suggests that we may be turning to techniques such as Bayesian estimation via the Gibbs sampler (Seltzer, 1990), which incorporates uncertainty about estimates of the variance components to obtain standard errors of estimates.

**SUMMARY**

Schooling occurs on multiple levels. Typically, the structure of multilevel models has followed the organizational structure of schools: students within classrooms within schools within districts within states within countries. Multilevel models capture effects identified with each of these levels, as well as interactions of effects across levels. Furthermore, many recent developments in estimation allow us to specify more complex multilevel models addressing a greater variety of outcomes and multiple sources of random effects.

But the social context of schooling is defined by relations among people. By studying the relations among the participants in schooling, we can begin to understand the processes through which individuals are affected by, and partially construct, schools as organizations and institutions. Institutions gain their salience as they are conducted into the school by teachers or students, and school cultures are formed through the accumulation of relations and influences among participants in schools. Our attention to these relations will require that we gather different forms of data and use quantitative methods to graphically represent relations among people as well as estimate effects on the selection of, and influence through, relations.

In the future, we may expect to see combinations of multilevel and social network models, including many we cannot now anticipate. These developments will help us understand the contexts in which students learn and teachers work. Most important, as quantitative methods become increasingly sophisticated mathemati-
cally, their application should help forge a link with others who study similar phenomena through alternate forms of inquiry.

NOTES

1 I define social context in terms of the aspects of schools as institutions and the relations among people within schools that affect the behavior of each individual affiliated with the school. In this sense, the definition is similar to other definitions put forth in this volume (see Salomon & Parkins, Chapter 1).

2 This database is the most recent in a succession of databases collected by the federal government. Beginning with the Project Talent data collected in the 1960s, the databases were improved to include longitudinal data and information about students, teachers, and administrators (National Longitudinal Study [1972] and High School and Beyond [1980]). The NELS (1988) database included information from students in eighth grade as well as more extensive information regarding their contexts as defined by parents and teachers.

3 Lee and Smith originally reported results in a metric allowing comparability across analyses of several outcomes and between models for intercepts and slopes in a single analysis. The results reported here have been reconverted into the original metric that represents gain in standardized achievement. Also, Lee and Smith estimated unique effects in schools that engaged in no reform practices using a separate dummy variable in Level 2 of their analyses, but these results are not reported here.

4 Based on the results and assumptions of the model in Lee and Smith, the intercepts in Figure 1 were generated to be normally distributed with variance 3.1 (approximate normal distribution was achieved by sampling random normal deviates and then modifying on the basis of visual inspection of a normal quantile plot). The variances and shapes of the distributions were established separately among the PCT and PCR schools, thus conforming with the assumption of homogeneity of variance of Level 2 errors (see Bryk & Raudenbush, 1992, p. 200). Similarly, the slopes were generated to be normally distributed with variance .45.

5 A notable exception is the finding in Lee and Smith (1991) that 50% of the variation in teachers’ salaries was between schools, but this is somewhat expected because teachers’ salaries are the result of large differences in region, urbanicity, and collective bargaining (Edwards, 1973).

6 In reviewing methods used for social network analysis, I use the general term actor, which may refer to a person, organization, country, and so forth.

7 The use of empirical criteria for defining subgroup membership also allowed me to establish procedures for determining the salience of the subgroup boundaries in terms of the pattern of relations. Specifically, because any clustering algorithm will identify some subgroups given even random data, I used Monte Carlo simulations to determine whether professional discussions were highly unlikely to be concentrated within the subgroup boundaries to the extent that they are in Figure 4 given the application of the algorithm to random data. In this case, there was less than a 1 in 100 probability of observing the concentration of discussions within the subgroup boundaries by chance alone. Furthermore, I established that the algorithm probably recovered most of the true subgroup memberships. The implication is that the subgroup boundaries were not merely imposed on a fluid pattern of relations but represented empirical tendencies in the teachers’ professional discussions.

8 I and others (Charles Bidwell and Pamela Quiroz) conducted interviews and observed teachers for several days and gathered a variety of official school documents (see Bidwell, 1998; Bidwell et al., 1997; Frank, 1993). In our interviews, our informants told us about (a) the distribution of authority and power in the school; (b) modes of decision making about curriculum, instruction, and student discipline; and (c) levels and directions of faculty involvement in these aspects of teachers’ work. In addition, we shadowed our teacher-informants during entire working days (usually 2 or 3 days per teacher), taking advantage of opportunities to observe formal and informal discussions between teachers and between teachers and administrators.
In Frank (1996), I noted that a comparable interpretation could not be sustained from an image constructed by embedding the boundaries of structurally similar blocks (two teachers are structurally similar to the extent that they engage in similar patterns of professional discussions) into a sociogram. While the use of structurally similar blocks has been common in other analyses, the concept and representation of cohesiveness capture the dense sets of relations that are key to characterizing the pattern of influence. In contrast, members of structurally similar blocks need not engage in relations with one another. The implication for interpretation is that there is not necessarily a concentration of influence within the block that produces commonalities in attitudes or orientations. The implication for the image is that the boundaries of the blocks overlap to the extent of being obscured. I argued that this result is consistent with longstanding theory. Although some have argued that actors who are structurally similar behave similarly (e.g., Burt, 1982; Merton, 1957; Nadel, 1957; Radcliffe-Brown, 1940; White et al., 1976), few have characterized organizations as composed of blocks of structurally similar people.

Note that this model has no intercept, because Mead (1967) argues that in estimating influence one may just as well subtract out the mean value of $y$ from all outcomes on the left- and right-hand sides of the equation. The specification of $w_{ii}$ should be carefully considered so as to define a model that generates realistic values of $y$ if implemented over time. For example, the standard approach is to “row normalize” each $w_{ij}$ by specifying $w_{*ij} = w_{ij}/(\Sigma_{r}w_{rj})$; thus, $w_{*ij} y$ represents the relative influence of $i'$ on $i$.

Frank and Fahrbach (1997) also considered differentiating between effects of information and influence to resppecify $w_{ij}$ to produce processes typically found in complex organizations, and Friedkin and Cook (1990) considered a “polarization” parameter to govern the processes implied by Equation 2 (see Friedkin & Marsden, 1994, for other possible specifications of Equation 2).

Burt (1991) and Wasserman and Faust (1994) have noted that the issue of significance testing in social network analysis requires serious consideration because one typically has data from the entire population rather than from a sample. Significance tests can be interpreted as an evaluation of phenomena sampled from a fixed time interval relative to a population of all phenomena over the duration of the system.

James Coleman is once again featured prominently in this area with regard to the definition and measurement of social capital and its application to effects in schools (Coleman, 1986; Schneider & Coleman, 1993).

### APPENDIX

#### Web Sites

For software availability, professional associations, publications, and web resources, etc., for multilevel models, refer to the Multilevel Models Project Web site based at the University of Montreal (comparable sites are available at the Institute of Education in London and the University of Melbourne):

http://www.medent.umontreal.ca/multilevel/

For software availability, professional associations, publications, Web resources, etc., for social network analysis, refer to the official Web site of the International Network for Social Network Analysis:

http://www.heinz.cmu.edu/project/INSNA/

### REFERENCES


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