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The Effects of High School Organization on Dropping Out: An Exploratory Investigation

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Abstract
Analyzes data from the High School and Beyond (HS&B) survey to investigate the effects of school characteristics on the probability of dropping out and absenteeism.

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The Effects of High School Organization on Dropping Out:

An Exploratory Investigation

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SUMMARY

There has been longstanding concern about students' failure to complete high school. In general, the rate of high school completion has increased over the past century. In the seventies, however, the trend reversed and dropout rates began to rise. In many central city high schools today, less than half of the students who enter ever graduate.

Most prior research has focused on the personal characteristics of dropouts, finding, for example, that Hispanic and Black students and students of lower socio-economic status are more likely to dropout. Dropouts also have lower grades and test scores and more absenteeism and discipline problems than students who complete high school. More recently, attention has been given to the differences in dropout rates among schools and how aspects of school organization might contribute to the problem.

This paper examines the effects of school characteristics on both the probability of dropping out and the strongest predictor of dropping out – absenteeism. The authors employ a sub-sample from the High School and Beyond (HS&B) data base which contains results of background questionnaires and standardized achievement tests given in 1980 to approximately 30,000 sophomores in 1100 public and private high schools. The students, both those still in school as well as those who had dropped out, were resurveyed two years later. Supplemental school data were also obtained from principal questionnaires.

The sub-sample used for this paper – 160 schools and 4450 students – was investigated using an analytic technique (*hierarchical linear modeling* or HLM) that permits examination of the impact of school-level factors on the relationship between student characteristics and absenteeism and dropping out.

The analysis reveals that absenteeism is less prevalent in schools where faculty are interested and engaged with students, and where there is an emphasis on academic pursuits. An orderly social environment is an important condition. Absenteeism is also lower in schools where there is less diversity among the student body in background characteristics and more commonality in the program taken by students. That is, schools that respond to diversity in the student body by differentiating program and curriculum have higher absenteeism rates. It is important to note that these internal diversity effects persist even after controlling for student-level differences in social class, sex, academic background, and race/ethnicity. Similar effects are related to dropout rates. Students are more likely to graduate from schools where there is an emphasis on academic pursuits, an orderly environment, and less internal differentiation.

Special benefits accrue to disadvantaged and at-risk youth from attending certain kinds of schools. A committed faculty, an orderly environment, and a school emphasis on academic pursuits are all associated with lower probability of dropping out for such youth. An important structural feature – smaller school size – also contributes to engaging disadvantaged students. The greater opportunity for informal face-to-face adult-student interactions in such contexts would seem to provide a compelling explanation for these results.

A number of questions remain unanswered, particularly with respect to large differences in dropout rates between public schools and the Catholic schools in the study. There is always the possibility that schools are successful because of student characteristics that are not captured by the available background measures. It might be argued, for example, that schools with lower dropout rates are able to sustain their particular organizational characteristics because of the preferable student populations that they serve. This "selection" effect is particularly an issue when comparing public and private schools, since students choose to attend the latter. However, because student characteristics shown by prior research to relate to absenteeism and dropping out are explicitly controlled for and because the school variables identified as important in this study overhelmed any differences in absenteeism between public and private schools, the conclusion about the importance of school organization and program are well-supported. Finally, HS&B core data does not permit analysis of all aspects of the school environment; for example, it includes no information from teachers. It is likely that improved measures of school factors would assist in the explanation of differences in dropping out between public and private schools.

The research reported here is another strand in a growing web of investigations which support the conclusion that the internal organizational features of schools can have significant educational consequences for all students, especially at-risk youth. Institutions whose structure and functioning coalesce around a sense of shared purpose create a coherent school life that is apparently able to sustain the engagement of students.

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Introduction

There has been longstanding concern about students' failure to complete high school. In general, the rate of high school completion has increased steadily over the past century. In the seventies, however, this trend reversed, and dropout rates began to rise (Wehlage & Rutter, 1986). In many central city high schools today, less than half of the students who enter ever graduate (Hess & Lauber, 1985). Although the potential economic, political and social consequences of this reversal are widely acknowledged (see for example, McDill, Natriello & Pallas, 1986), the origins of this problem remains unclear.

Most prior research has focussed on the personal characteristics of the dropout. Major studies here include Bachman, Green, and Wirtanen (1971), Children's Defense Fund (1974), Rumberger (1983), Pallas (1984), and Coombs and Cooley (1986). Ekstrom, Goertz, Pollack and Rock (1986) provide the most comprehensive and current information. Background characteristics of students are strongly related to dropping out. Hispanics and Blacks, lower SES students, and students from households with few educational resources are more likely to dropout. Dropouts also exhibit different attitudes and behaviors while still in school. They have lower grades and test scores, are more often absent, do less homework, have more discipline problems, and are generally alienated from school life.

Implicit in much of this research has been the assumption that dropping out is a problem of the individual student, and that understanding the characteristics of dropouts will help educators target resources in ways that will reduce the number of those who dropout in the future. Identifying the attitudinal and behavioral correlates of dropping out can provide a basis for identifying youth who are *at-risk* in this regard.

Until recently, little attention has been given to the differences in dropout rates among schools and how aspects of school organization might contribute to this problem. Coleman and Hoffer (1987) report substantial differences in dropout rates between public and Catholic schools. Even after adjusting for student characteristics, the probability of dropping out is substantially less in the Catholic than in the public sector. Furthermore, Catholic schools appear especially effective for at-risk students who have had a history of discipline problems in high school.

Coleman and Hoffer, however, find that these sector effects on dropping out are external to the school. They hypothesize that functional communities organized around parish churches bring parents and students together, promoting greater face-to-face social interaction across the generations, and thereby creating a form of social capital which facilitates the work of the school. While the idea has much appeal, Coleman and Hoffer provide no direct empirical evidence that the hypothesized social relations among school families actually characterize Catholic high schools. Their argument is based on an assumption that Catholic high schools largely draw their student populations from a single parish. Although this is a reasonable assumption about Catholic elementary schools, only 13% of Catholic high schools are attached to a single parish (NCEA, 1985). The vast majority are either private or diocesan and draw their students from diverse geographic areas. This fact raises doubts about the validity of the functional community explanation.

Nevertheless, Coleman and Hoffer's research does indicate that there are substantial differences in student dropout rates between schools in the public and Catholic sectors. Further, the source of these school effects on dropping out remain largely unexplored.

Wehlage and Rutter (1986) is the only published research which has approached the problem of dropping out from a school organizational perspective. Unfortunately, the Wehlage and Rutter investigation was limited in some significant ways. The "school variables" considered in their research were individual student reports about their attitudes toward school and their behavior inside and outside of school. No attempt was made to explore the effects of school-level measures of structure and normative environment, and all analyses were conducted at the individual student level. It is well known, however, that student-level analyses can be highly misleading in research on school effects.[1] While Wehlage and Rutter conclude that weak adult authority, a climate of truancy and low expectations, large school size, and an absence of caring adult relationships and of stimulating curriculum contribute to dropping out, the empirical support for these conclusions remain suspect.

This paper builds on the exploratory work of Wehlage and Rutter to investigate directly the effects of structural and normative features of schools on both the probability of dropping out and the strongest behavioral predictor of dropping out, absenteeism. We are concerned about both average differences among schools in these outcomes, and the differential effects that schools may have on these outcomes for different types of students. Although prior research has clearly established that disadvantaged and at-risk youngsters are much more likely to dropout, we hypothesize following Coleman and Hoffer (1987) that the strength of these relationships vary across schools depending upon the nature of their social organization. A hierarchical linear model analysis (Raudenbush & Bryk, 1986) is used in order to investigate these distributive questions.

Theoretical Orientation

The fragmentation of human experiences and the resultant individual alienation is a central theme in modern social theory. In directing this critique toward schools, Bowers (1985) has argued that the nihilistic quality of contemporary school environments tend to deny meaning to human action and foster disillusionment and a sense of unrootedness and anomie. Newmann (1981) dwells more specifically on structural aspects of the organization of instruction and the nature of human relations within schools. He claims that these school features can affect students' subjective states, such as their sense of estrangement. He notes that both adolescence and youth are critical developmental periods during which individuation must be balanced by social integration within a community. Yet questions about how school policies and procedures might foster positive social integration for students has received little explicit attention. Newmann suggests that developments in school organization

[1] For a review of these methodological problems, see Burstein (1980a; 1980b).

over the past twenty-five years, such as larger school size, increasing specialization of staff and diversification of curriculum, have contributed to a heightening of student alienation.

Theoretical arguments such as these direct attention toward the possible effects of school structure and normative environments on dropping out. The literature referenced in the introduction suggests that dropping out is not a spontaneous decision but rather a gradual drifting away from the school as a locus of students' daily activities. Potential dropouts are likely to enter high school academically disadvantaged and somewhat distant socially from other students. This initial distance can be amplified by a curriculum structure of many choices which results in considerable differentiation among students within a school in terms of their subsequent academic experiences (Cusick, 1983; Powell, Farrar & Cohen, 1985; Oakes, 1985). The effects of this structural differentiation are further exacerbated by weak normative environments where little effort is expended to enhance the human engagement of students and faculty (Grant, 1985a; 1985b). From this perspective, the act of dropping out is an end-point of a process of increasing academic and social distance from the mainstream of school life.

Clearly, student alienation is a result of social-economic forces that reach far beyond the school. To be sure, schools are not the primary culprit. Rather, the claim is that the broad cultural change of the past two decades have also had a direct effect on the organization of contemporary schools, and these changes in turn have had a major impact on student engagement (Sizer, 1984; Powell et al., 1985; and Grant, 1988). Specifically, we hypothesize that the increased differentiation in student experiences which results from a "shopping mall" curriculum and the weaker normative environments of the contemporary high school contribute to problems of absenteeism and dropping out.

Public-Catholic sector comparisons provide a useful natural experiment for investigating this proposition. The differences in dropout rates between the two sectors are quite large. Field research on Catholic high schools (Bryk, Holland, Lee & Carriedo, 1984; NCEA, 1986) indicates substantial differences in the internal organization of these schools as compared to the modern comprehensive public high school. The typical Catholic high school has a structured academic program than fosters greater commonality of academic experiences among students. The effects of this common ground of shared activities are further enhanced by social relations among both adults and students characterized by human caring and personal interest. And all of this is more likely to occur within an institutional environment that is peaceful, orderly, and one that emphasizes academic pursuits.

If the internal organization of schools has a substantial impact on student alienation in the ways specifically suggested above, then we would expect that much of the observed Catholic sector effects would be largely explained away once these organizational variables are taken into account. Thus, in the analyses reported below, we model the effects of selected measures of school organization and environment on dropping out and student absenteeism. We also examine whether such a model can account for the observed sector differences on these two outcomes. A positive result would strengthen the argument that organizational features of schools have substantial effects on student engagement.

Methodology

Data

In this study, we employ the High School and Beyond (HS&B) data base, a general purpose survey of American high schools. The HS&B data on the 1980 sophomore cohort provides a nationally representative longitudinal data on high school dropouts. In the base year (1980), questionnaires and standardized achievement tests were administered to a stratified random sample of approximately 30,000 sophomores in 1100 high schools. The students, both those still in school as well as those who subsequently dropped out, were resurveyed two years later. Supplemental school data were also obtained from principal questionnaires.

Our analyses are based on a sub-sample of the HS&B sophomore longitudinal cohort. Since the public and Catholic sectors also differ across a wide range of school organizational features, a school-level sub-sample was drawn in order to preserve the ability to investigate cross sector differences. Specifically, all Catholic high schools (83) and a random sub-sample of public high schools (94) were selected for this investigation. All students within these schools who were surveyed in the sophomore base year data collection (a maximum of 36 per school) were included. Because of missing data at the school level, the final analytic sample was reduced to 160 schools and 4450 students.

Variable Specification

A conceptual strength of an HLM analysis is the clear distinction made between student- and school-level variables. The school is an important organizational unit that is directly represented in the analysis. While the outcome variables are specified at the student level, the predictors include of both student- and school-level measures.

Outcome variables. We conceive of dropping out as an asymptote, or end result of, chronic truancy. Thus, early absenteeism (e.g. at grade 10) represents an important intermediate outcome of interest. In fact, early absenteeism is the strongest student-level predictor of dropping out ($r = .27$). For this reason, we chose to investigate possible school effects on both absenteeism at grade 10 and dropping out. Specifically, we define as outcome variables:

LOGABSNT natural log of the number of days absent but not ill, +1, an interval scale version of HS&B BB016;

DROPOUT student status at the 1982 follow-up survey (1=dropout/0=in school or early graduation) The definition of a dropout in HS&B does not include students who may have left school prior to the spring of their sophomore year (i.e. the baseline data collection point in HS&B). Further, some of the students who were marked as dropouts in 1982 eventually returned to complete school.

For purposes of this study, however, any student who was out of school but not graduated in the spring of 1982 was considered a dropout.

Student-level predictors. As noted in the introduction, research has documented race/ethnicity, sex, and social class effects on dropping out. Academic difficulties prior to high schools and at-riskness behaviors early in high school are also important determinants. Specifically, we conceive of students' school experiences as a progression consisting of possible difficulties in elementary school (ACADBKGD), leading to behavioral and attitudinal problems early in high school (ATRISK) and absenteeism (LOGABSNT), and eventually resulting in the act of dropping out of school altogether (DROPOUT). The specific measures constructed were:

- ACADBKGD a factor composite of HS&B variables which indicates if respondent had taken remedial math and/or English in grades 9 or 10 (BB011A or BB011B), had plans at grade 8 to attend college (BB068A), had been read to before starting school (BB095), and had ever repeated a grade in elementary school (FY59).
- ATRISK a factor composite that combines attitudinal and behavioral correlates of at-riskness: pupil has experienced disciplinary action (BB059B), suspension (BB059D), cut classes (BB059E), trouble with law (BB061A), poorer grades (BB007), dissatisfied with education (BB059A), disinterested in schooling (BB059C), and does not like working hard (BB061E);
- BLACK a dummy variable (1=Black/0=Other);
- HISPANIC a dummy variable (1=Hispanic/0=Other);
- SES a linear composite of five elements: father's occupation, father's and mother's education, family income, and an index based on eight household possessions (each item is weighted equally); and
- SEX a dummy variable (1=Female/0=Male).

School-level measures. We grouped school variables into five different categories, as detailed below. The first three categories capture different aspects of a school's normative environment. Set one focuses on students' and principals' perceptions of teachers in terms of their commitment to the school and involvement with students. Both Rutter et al. (1979) and more recently Grant (1988) point toward the important role that teachers play in establishing an ethos which sustains students' engagement in school life. The next two sets focus on school climate in terms of academic press and order/discipline. These factors have demonstrated effects on academic achievement (see for example Coleman, Hoffer & Kilgore, 1982; Hoffer, Coleman & Greeley, 1985; and Coleman & Hoffer, 1987), and also contribute to the weaker relationship in the Catholic sector between student background and academic outcomes (Lee & Bryk, 1988a). Although there are reasons to worry that school emphases on order, discipline and academic work might exacerbate absenteeism and dropping out, there is evidence that higher standards for student behavior and performance can encourage student effort, discourage absenteeism and reduce the probability of dropping out (for a review see McDill, Natriello & Pallas, 1986). The fourth set consists of a set of measures that focus on the commonalities and differences among students' courses of study with a school. As noted earlier, differences in students' classroom experiences may amplify the initial academic and social differences that students bring to the high school, and as a result exacerbate problems of absenteeism and dropping out. The last set consists of school compositional variables. These are proxy measures of school communities and peer relations that may also contribute to a school's normative environment.

I. Perceived Teacher Quality and Interest in Students:

STFPBLM principal's report about staff absenteeism and lack of commitment and motivation (SB056E, F);

PCDQLTCH a factor composite of student reports about the percentage of their teachers who enjoy their work, make clear presentations, work students hard, treat students with respect, are witty and humerous, don't talk over students' heads, are patient and understanding, return work properly, and are interested in students outside of class (school-level average of student factor scores from the FY68 series).

II. The Academic Press in the School Environment:

AVHMEWRK hours per week students spend on homework (school average of BB015);

AVGDEATT students' attitudes toward getting good grades (school average of YB052AA, AB);

AVINTRA students' interest in school, mathematics and English (school average of student factor scores from a composite of BB008AB, AC, BB, BC, and BB059C);

AVLACKAC students' reports about lack of academic press in the school (school average of EB035A);

ACADEMP school average of scores from a factor composite of student concentration in academic pursuits: average number of math (FY5A-E) and science (FY5F, G) courses taken, percentage in honors programs (FY9C, D), percentage in remedial programs (FY9A, B), percentage in general program (FY2).

III. The Disciplinary Climate of the School:

SAFE percentage of students who feel safe in the school environment (based on BB059F);

AUTHRTY students' ratings of the fairness and effectiveness of discipline within the school (BB053F, G averaged to school level);

CLMFAC a school level composite index based on: i) students' reports about the incidence of students talking back to teachers, refusing to obey instructions, attacking teachers and fighting with each other (school average of student factor score based on the YB019 series); ii) the school average of students' reports about their own discipline problems in school, suspension, probation and cutting class (school average of student factor scores based on BB059B-E); and iii) a factor score from principals' reports about the extent of problems in the schools from physical conflict among students, conflicts between teachers and students, theft, vandalism, rape, possession of weapons, verbal abuse of teachers, and drugs and alcohol (SB056 series);

SCHSPIRIT an average of students' ratings of school spirit (FY67I).

IV. Curricular Differentiation and Commonality:

AVMTHEMP average number of advanced mathematics courses (beyond algebra I) taken in the school (FY5B-E). (This is an indicator of the commonality of students' academic work.)

SDMTHEMP standard deviation of the number of advanced math courses taken (sum based on FY5B-E) within each school (a measure of academic differentiation for the school);

CURDVST a school-level measure of the total differentiation in student academic course-taking experiences. This is another measure of the academic differentiation within the school based on student reports of the number of science, mathematics, foreign language and English courses taken (FY4A-H), based on the sum of squares of the deviations of individual student course plans from the school mean for each content area and summarized in a mean-squared metric;

AVACDPGM percentage of students in the academic program (another indicator of the commonality of academic pursuits).

V. Social and Academic Background Composition of the Schools:

SCHSES the average social class of students within the school (school average of student SES variable);

SDSES the standard deviation of social class, SES, within each school (a measure of social differentiation);

SCHATRSK the average at-riskness of students within the school (school average of ATRISK);

SDATRSK the standard deviation of at-riskness within each school (a measure of at-riskness differentiation);

HIMNRTY a dummy variable enrollment in excess of 40% minority (Black and/or Hispanic);

AVADBGD school average of the student variable, ACADBKGD;

SIZE school size, also considered as part of factor IV (SB002A).

Correlations for both the student- and school-level variables with the two outcomes are displayed in Tables 1a and 1b. Among the student-level variables, the correlations for sex, race/ethnicity, and academic backgound with dropping out and absenteeism are weak ($< .10$), although in the expected direction. The correlations with social class are somewhat larger (.156 and .116 respectively), and the strongest relations are with the at-riskness measure (.220 and .319).

The correlations for the school-level variables with the school means for the two outcomes follow the hypothesized pattern. Mean absenteeism and school dropout rates are lower in high SES schools (SCHSES) where students enter well prepared (AVACBGD) and have positive perceptions about their teachers (PCDQLTCH), where there is a strong academic emphasis (AVHMEWRK, AVINTRA, ACADEMP, AVMTHEMP, AVACDPGM), and orderly environment (SAFE, AUTHRTY). Absenteeism and dropout rates are higher in bigger schools (SIZE), in schools where there is a high incidence of at-riskness (SCHATRSK), where principals report problems with staff (STFPBLM), where academic expectations are weak (AVLACKAC), the incidence of discipline problems is great (CLMFAC), and student bodies are more differentiated in terms of social class (SDSES), at-riskness (SDATRSK), and academic experiences (CURDVST).

The General Hierarchical Linear Model

As noted in the introduction, there is some evidence that the effects of individual schools on student truancy or dropping out may vary for different types of students. This proposition implies the existence of interactions between student- and school-level variables. It has been shown, however, that hypotheses about such cross-level interactions are difficult to assess with conventional statistical methods. Traditional single-level analyses have produced seriously flawed inferences (Cronbach, 1976; Burstein, 1980a; 1980b). Raudenbush and Bryk (1986) demonstrated that alternative analytic techniques, called hierarchical linear models (HLMs), are ideally suited for evaluating such cross-level hypotheses.

Under the HLM framework, a clear conceptual distinction is made between student-level and school-level relations. This conception is reflected in the two models that make up a two-level HLM.[2] The first model captures the primary relationships at the student level within each school. The second model attempts to explain these student-level relationships in terms of school-level factors. We outline below a brief overview of the HLM and its estimation. Further details are provided in Appendix A.

In the application which follows, the within-school model represents the amount of absenteeism and drop-out status for student i in school j, Y_{ij}, as a linear function of various student background characteristics, X_{ijk}, and random error, ϵ_{ij}:

$$Y_{ij} = \beta_{j0} + \beta_{j1}X_{ij1} + \beta_{j2}X_{ij2} + \cdots + \beta_{j(p-1)}X_{ij(p-1)} + \epsilon_{ij} \,, \tag{1}$$

where $i = 1, 2, ..., n_j$ and $j = 1, 2, ..., N$. $k = 0, 1, 2, ..., p-1$ indexes the student-level covariates. The β_{jk} regression coefficient indicates how student outcomes in school j are distributed with regard to measured student characteristic such as academic background,

[2]The same reasoning applies to data structures with more than two nested levels.

Table 1a

Correlations of Student-level Covariates with Dropping Out and Absenteeism (4450 Students)

	DROPOUT	LOGABSNT
SEX	-0.030	-0.032
HISPANIC	0.050	0.037
BLACK	0.035	0.013
SES	-0.156	-0.116
ATRISK	0.220	0.319
ACADBKGD	-0.097	-0.038

Table 1b

Correlations of School-level Covariates with Dropping Out and Absenteeism (160 Schools)

	School Means	
	DROPOUT	LOGABSNT
SCHSES	-0.357	-0.348
SCHATRSK	0.475	0.620
STFPBLM	0.251	0.271
PCDQLTCH	-0.123	-0.244
AVLACKAC	0.197	0.329
AVHMEWRK	-0.398	-0.580
AVGDEATT	0.041	-0.032
AVINTRA	-0.176	-0.305
ACADEMP	-0.437	-0.540
AUTHRTY	-0.095	-0.403
SCHSPRIT	-0.053	-0.212
CLMFAC	0.419	0.607
SAFE	-0.219	-0.266
AVMTHEMP	-0.395	-0.406
SIZE	0.144	0.233
CURDVST	0.200	0.163
AVACDPGM	-0.473	-0.537
HIMNRTY	0.129	0.003
SDSES	0.222	0.147
SDATRSK	0.206	0.357
AVACBGD	-0.287	-0.335

sex, race/ethnicity, or social class. Equation 1 may be viewed as a measurement model of the effects of school j on the students within it. Rather than simply assuming that a school has a constant effect on all of its students, as in conventional analyses, this model allows us to represent differential effects for different types of students.

A distinctive feature of the HLM is that the school-level regression coefficients, β_{jk}, are presumed to vary across schools, and it is this variation which is of particular interest. Therefore, we formulate a set of between-school equations which represents each of the regression parameters as a function of school-level variables, Z_{jl}, and a unique residual school effects, v_{jk} :

$$\beta_{jk} = \gamma_{0k} + \gamma_{1k}Z_{j1} + \gamma_{2k}Z_{j2} + \cdots + \gamma_{(q-1)k}Z_{j(q-1)} + v_{jk} , \tag{2}$$

where $l = 0, 1, 2, ..., q-1$. Equation 2 models the effects of school variables on the distribution of outcomes within schools. The γ coefficients represent the influence of specific school-level variables on how effects are distributed among different types of students within a school. For example, suppose that β_{j1} is the regression coefficient of dropping out on students' social class. The size of this coefficient measures the extent to which initial social class differences among students are related to the probability of dropping out within a school. We hypothesize that variation in the strength of this relationship across schools depends on aspects of school organization and normative environment. This is represented in Equation 2 by the inclusion of specific school-level variables, Z_{jl}, to model the social class differentiation effect, β_{j1}. The γ coefficients in this equation indicate how school characteristics either amplify or attenuate social differentiation within schools in the probability of dropping out.

In order to facilitate interpretation of the HLM results presented in the next section, all school-level variables, except for SECTOR and HIMNRTY which are dummy variables, have been standardized. As a result, the magnitude of the γ coefficients can be directly compared in assessing the relative contributions of the school-level variables in each of the school effects models.

Statistical Estimation

One obvious difficulty with estimating the parameters of the between-unit model is that the outcome variables, β_{jk}, are not directly observed. They can be estimated using standard methods such as ordinary least squares, but these estimates, $\hat{\beta}_{jk}$, contain error that is given by

$$\hat{\beta}_{jk} = \beta_{jk} + \delta_{jk} . \tag{3}$$

Substituting from Equation 3 into Equation 2 for β_{jk} yields an equation in which the estimated relation, $\hat{\beta}_{jk}$, varies as a function of measurable characteristics and a random error equal to $v_{jk} + \delta_{jk}$:

$$\hat{\beta}_{jk} = \gamma_{0k} + \gamma_{1k}Z_{j1} + \gamma_{2k}Z_{j2} + \cdots + \gamma_{(q-1)k}Z_{j(q-1)} + v_{jk} + \delta_{jk} . \tag{4}$$

Equation 4 resembles a conventional linear model except that the structure of the error term is more complex. A consequence of this more complex error term is that neither the γ coefficients nor the covariance structure among the errors can be appropriately estimated with conventional linear model methods. However, recent developments in statistical theory and computation now make this estimation possible. (See Appendix A for more details).

The HLM estimators have several important properties. First, the precision of the $\boldsymbol{\beta}_j$ coefficients estimated in any unit j depend upon the amount of data available on that unit. In estimating the γ coefficients, HLM methods weight the contribution of the individual β_{jk} proportional to their precision. This optimal weighting procedure minimizes the effects of the sampling variance on inferences about key model parameters. Second, the estimation procedures are fully multivariate since they take into account the covariation among the $\boldsymbol{\beta}_j$ coefficients. To the extent these parameters do covary, estimation will be more precise.

Third, HLM estimation enables the investigator to distinguish between variation in the true parameters, β_{jk}, and the sampling variation which arises because $\hat{\beta}_{jk}$ measures β_{jk} with error. That is, from Equation 3,

$$Var(\hat{\beta}_{jk}) = Var(\beta_{jk}) + Var(\delta_{jk}) \,. \tag{5}$$

The total observed variance is simply the sum of the variance of the random parameter and its sampling variance. Knowledge of the amount of parameter variability is important in the process of formulating HLMs and in evaluating their results since it is only parameter variance that can be explained by school factors.

General Analytic Approach

We began our analyses by developing separate HLMs for each of the five school-level factors described above. This provided our first look at the relative effects of each factor, and also identified the specific variables within each factor that were most strongly related to absenteeism and dropping out. We then proceeded to develop a composite model based on the most significant variables from all five factors.

In general, absenteeism and dropping out are much less prevalent in the Catholic sector. We expected the estimated sector effects to become smaller as we enter specific school-level factors into our model, assuming our theoretical formulation was correct. Our goal was to construct a model that accounted for the sector differences on absenteeism and dropping out since such a model adds credibility to the claim that the specific school-level variables included in the model are causally linked to these outcomes.

Analyses and Results

Modeling Absenteeism

Specification of within-school model. Our first analysis considered a within-school model, equation (1), with LOGABSNT as the student-level outcome and SES, SEX, BLACK, HISPANIC, and ACADBKGD as predictors. The intercept and the regression slopes for each predictor variable were allowed to vary across schools. We posed an unconditional between-school model for each of these parameters, i.e., no school-level variables were specified in equation (2). This model was useful for estimating the total parameter variance in the six random effects (the intercept and five regression slopes), and for examining the appropriateness of the within-school model. The residuals from this model allowed us to examine the variability in the random effects and to test a homogeneity hypothesis for each parameter.

The homogeneity hypothesis was sustained for the SES, SEX, BLACK, and HISPANIC slopes. From a technical point of view, this means that there was no indication in the data of stable differences across schools on these particular regression coefficients. Schools do not appear to differ in the way absenteeism is distributed with regard to sex, social class, and race/ethnicity. The result of the homogeneity test for ACADBKGD was significant ($p = .02$). Examination of the variability in the ACADBKGD slopes indicated that two schools had considerably larger slopes than the rest of the sample. When these two were deleted, the homogeneity statistic was no longer significant. This result suggested that in subsequent models we estimate a common regression slope for ACADBKGD as well. Thus, we settled on the following within-school model for our examination of absenteeism:

$$y_{ij} = \beta_{j0} + \sum_{h} \beta_h (X_{ijh} - X_{..h}) + \epsilon_{ij} \ , \qquad (6)$$

where $h = 1, 2, ..., 5$ indexes the variables SEX, SES, BLACK, HISPANIC, and ACADBKGD and $X_{..h}$ denotes the appropriate grand mean.

This model differs from equation (1) in that we have specified a common regression slope for all schools for the effects of SEX, SES, BLACK, HISPANIC, and ACADBKGD. In HLM terminology, the effects of these variables are treated as *fixed*. (This is analogous to the homogeneity of regression assumption in analysis of covariance.) The intercepts in equation (6), however are treated as *random* since the results of our unconditional model indicated substantial heterogeneity on this parameter ($p < .001$). We refer to equation (6) as a *random intercept model*, which is an important special case. If we deviate each of the independent variables in (6) around their respective grand means, the intercept represents the absenteeism rate for each school after adjusting for differences among schools in the types of students they enroll in terms of sex, social class, academic background, and race/ethnicity. These adjusted school absenteeism rates are similar to the adjusted means produced in an analysis of covariance. The HLM estimates of β_{j0}, however, takes into account the varying precision of the individual school rates, and the standard errors of β_{j0} reflect the random character of these rates. Neither of these factors are taken into account in the traditional ANCOVA.

Table 2

Variances in School Absence Rates

Total parameter variance in school absence rates	.0598
Parameter variance in school absence rates after adjusting for SES, SEX, BLACK, HISPANIC, ACADBKGD	.0481
Percentage of school-level variance attributable to differences in student background	19.6 %

Table 3

Sector Effects on
Adjusted School Absence Rates

Variable	Coefficient	Std. Error
Base Absenteeism Rate	.969	.025
SECTOR	-.317	.037
STUDENT-LEVEL CONTROLS		
SES	-.055	.015
SEX	-.030	.026
HISPANIC	.071	.041
BLACK	-.088	.054
ACADBKGD	-.031	.013
Percentage of School-Level Variance attributable to SECTOR effects		40.8 %

The parameter variance (see Equation 5) in school absence rates, LOGABSNT, is .0598 (see Table 2). This is estimated by specifying a within-school model that only includes a random intercept for each school:

$$y_{ij} = \beta_{j0} + \epsilon_{ij} \ . \tag{7}$$

Clearly, part of the variability among schools in their absenteeism rates results from the different types of students that schools enroll. When we estimated a within-school model that adjusts for differences in social class, sex, academic background, and minority status, as in equation (6), the variability in school absence rates declined to .0481. Comparison of the results from (6) and (7) indicates that 19.6% of the school-level variance in absence rates is attributable to differences in the background characteristics of students enrolled in various schools. The remainder is potentially explainable by the school-level factors listed above. (Other unspecified student-level differences could also account for some of this variability.)

Sector effects on adjusted school absence rates. Table 3 presents the results from an HLM where SECTOR (0=public/ 1=Catholic) has been introduced into the between-school model:

$$\beta_{j0} = \gamma_{00} + \gamma_{10} Z_{j1} + u_{j0} \ ; \tag{8}$$

where Z_{j1} is the SECTOR dummy variable. The absenteeism rate in public schools after adjusting for student-level differences in race/ethnicity, sex, social class, and academic background is .969. (This is the *base absenteeism rate* in Table 3.) The sector effect of -.317 means that the average absenteeism rate in the Catholic schools is about a third less than in the public sector. These sector differences account for 40.8% of the school-level variance in this sample. In terms of the student-level predictors, lower SES students and those with a weak academic background are much more likely to be absent. The same is true for Hispanic. There is no evidence of significant sex differences or different absenteeism rates for Black students.

Separate effects of five school-level factors. Table 4 presents the results from fitting separate between-school models for each of the five school factors: Teacher Quality, Academic Press, Disciplinary/Social Climate, Curriculum Organization, and Composition. Focusing first on the results for models without SECTOR, each of the five factors explains a significant portion of the variance in school absence rates. The strongest effects are associated with the Disciplinary/Social Climate and Academic Press. The estimated coefficients are consistent with previous school effects research. Absenteeism is higher in schools where there is a greater incidence of discipline problems (CLMFAC). It is lower in schools where students feel safe (SAFE) and perceive discipline to be fair and effective (AUTHRTY). Absenteeism is also lower in schools where there is a strong press toward doing homework (AVHMEWRK), getting good grades (AVGDEATT), an interest in academics (AVINTRA) and a concentration of students in academic pursuits (ACADEMP).

Students' perceptions of teacher quality (PCDQLTCH) is also associated with lower absenteeism rates. Where principals report problems with staff (STFPBLM), the rates are

Table 4

Comparison of Alternative Models
for School Absence Rates

	School-level Factor	Variables	Model without SECTOR Coeff.(S.E.)	SECTOR added last Coeff.(S.E.)
I	Teacher Quality	Base Absenteeism Rate	.831 (.021)	.946 (.027)
		STFPBLM	.072 (.022)	...
		PCDQLTCH	-.090 (.020)	-.045 (.020)
		SECTOR		-.269 (.045)
		% Variance Explained	12.9	39.7
II	Academic Press	Base Absenteeism Rate	.807 (.018)	.884 (.033)
		AVHMEWRK	-.057 (.026)	-.056 (.025)
		AVGDEATT	...	-.042 (.021)
		AVINTRA	-.044 (.026)	...
		AVLACKAC	...	...
		ACADEMP	-.109 (.026)	-.059 (.031)
		SECTOR		-.169 (.060)
		% Variance Explained	46.6	51.4
III	Disciplinary/ Social Climate	Base Absenteeism Rate	.856 (.017)	.955 (.026)
		CLMFAC	.150 (.017)	.118 (.018)
		AUTHRTY	-.035 (.016)	...
		SAFE	-.036 (.020)	...
		SCHSPIRIT	-.024 (.016)	...
		SECTOR		-.223 (.044)
		% Variance Explained	59.3	63.2
IV	Curriculum	Base Absenteeism Rate	.815 (.023)	.882 (.032)
		CURDVST	.056 (.019)	.046 (.018)
		AVACDPGM	-.133 (.025)	-.107 (.026)
		AVMTHEMP	...	...
		SIZE	...	...
		SECTOR		-.163 (.057)
		% Variance Explained	33.7	43.0
V	Composition	Base Absenteeism Rate	.849 (.026)	.934 (.030)
		SDSES	.094 (.022)	.080 (.020)
		AVACBGD	-.073 (.024)	-.042 (.023)
		HIMNRTY	...	...
		SCHSES	-.078 (.030)	...
		SIZE	.042 (.024)	...
		SECTOR		-.237 (.049)
		% Variance Explained	21.6	40.3

(...) the t-ratio of coeff./S.E. is less then 1.5.

higher. The results from the Curriculum and Composition factors suggest both average internal diversity and composition effects. Absenteeism rates are lower in schools where students enter with stronger academic backgrounds (AVACBGD) and where a high percentage are enrolled in an academic program (AVACDPGM). Absenteeism rates are higher where there is more diversity among students' academic experiences (CURDVST) and social background (SDSES). It is important to note that these internal diversity effects persist even after controlling for student-level differences in social class, sex, academic background, and race/ethnicity.

Table 4 also presents results when SECTOR is added to each of the models. In general, the overall pattern of results remains the same, but the magnitude of the effects of the school-level variables becomes smaller because of the confounding between these school variables and SECTOR. Although the estimated sector effects under each model are smaller than the overall effect reported in Table 3, significant sector differences persist. This means no one of these factors taken alone can account for the differences between sectors in absenteeism rates.

A composite model for absenteeism. Table 5 presents the results of a composite model that does explain the differences between sectors in absenteeism. This model was developed by taking the subset of variables from each factor in Table 4 that had t-ratio's of at least 2.0 after SECTOR was included. In the initial estimation of the composite model, some of these variables were no longer significant. These were deleted and the reduced model reestimated. The final composite model includes variables from all five factors. Absenteeism rates are lower in schools where perceived quality of teaching is high (PCDQLTCH), where there is a strong academic press in terms of doing homework (AVHMEWRK) and a concentration of students in academic pursuits (ACADEMP), and where the incidence of disciplinary problems (CLMFAC), internal curricular diversity (CURDVST) and social class diversity (SDSES) are all low. Taken together these variables explain 66.9% of the school-level variance in absenteeism rates.

Modeling Dropping Out

Our analyses for dropping out followed that same general strategy that we employed for absenteeism. Although DROPOUT is a dichotomous outcome we have treated it as if it were continuous. Despite well known technical problems, there is a long history of use of such linear probability models in econometrics because of their computational efficiency over alternative methods such as logit and probit analysis (Amemiya, 1985). Although a logit model has been developed for multilevel analysis (Stiratelli, Laird & Ware, 1984; Wong & Mason, 1986; Thum, 1987), the computational demands are especially intense because two independent iterative processes are required.[3] Given the exploratory nature of this study, the use of such estimation routines were simply not feasible.

Within-school model. In addition to the student-level variables considered in mod-

[3] These methods are especially burdensome when the number of schools is large (e.g., $N > 50$).

Table 5

A Composite Model that Accounts for Sector Differences in School Absence Rates

Variables	Model Coeff.	Model S.E.	SECTOR added last Coeff.	SECTOR added last S.E.
Base Absenteeism Rate	.831	.017	.859	.031
PCDQLTCH	-.056	.017	-.053	.017
AVHMEWRK	-.055	.022	-.055	.022
ACADEMP	-.051	.025	-.031	.030
CLMFAC	.097	.019	.097	.019
CURDVST	.024	.016	.020	.017
SDSES	.027	.020	.026	.020
SECTOR			-.059	.054
STUDENT-LEVEL CONTROLS				
SES	-.045	.015	-.046	.015
SEX	-.010	.026	-.009	.026
HISPANIC	.057	.041	.059	.041
BLACK	-.080	.052	-.083	.052
ACADBKGD	-.029	.013	-.029	.013
$\%\Delta R^2$		66.9		67.6

Table 6

Variances in School Dropout Rates and Differentiating Effects with Regard to Social Class and At-Riskness

	Base Dropout Rate	Differentiating Effects SES	Differentiating Effects ATRISK
Total parameter variance	.00435	.00106	.00147
Parameter variances in school effects adjusting for student's ACADBKGD, HISPANIC, BLACK, SEX	.00411	.00106	.00144
Parameter variances in school effects after also adjusting for compositional effects of school social class and at-riskness	.00260	.00102	.00144
Percentage of total parameter variances attributable to student background, school social class and at-riskness	40.2 %	3.8 %	2.0 %

eling absenteeism, we included ATRISK in the within-unit model. Each of the components of this factor composite has been identified in the literature as an important predictor of dropping out, and the composite measure has the strongest association of any of the student-level variables with dropping out ($r = .220$).[4]

Our preliminary analyses indicated that the individual school slopes for race/ethnicity (BLACK, HISPANIC) and academic background (ACADBKGD), do not appear to vary across schools (i.e., the homogeneity of regression slopes was sustained for these variables). Thus we decided to *fix* the effects of ACADBKGD, BLACK, and HISPANIC. Our final within-school model for dropping out was:

$$y_{ij} = \beta_{j0} + \sum_k \beta_{jk}(X_{ijk} - X_{\cdot jk}) + \sum_h \beta_h(X_{ijh} - X_{\cdot\cdot h}) + \epsilon_{ij} \, , \tag{9}$$

where $k = 1, 2$ indexes the random effects of SES and ATRISK, and $h = 3, 4, 5$ indexes the fixed effects of ACADBKGD, BLACK, and HISPANIC. β_{j0} is the mean dropout rate for school j, adjusted for differences among schools in students' academic background and minority composition. We will refer to this as the base dropout rate in school j. β_{j1} represents the differentiating effect of students' social class on the probability of dropping out in school j. β_{j2} measures the differentiating effect with regard to at-riskness. In schools where the β_{j1} and β_{j2} slopes are large, the low SES and at-risk student is much more likely to drop out.

Table 6 displays estimates of the total parameter variance in the three school effect measures, and the residual parameter variances in these measures after controlling for student background characteristics, and compositional effects of school social class and mean level of at-riskness. These control variables account for a substantial percentage of variance in base dropout rates (40.2%), but only a negligible portion of the variation in social class and at-riskness differentiation (3.8% and 2.0% respectively).

Among the student-level control variables, only SEX is significantly related to dropping out. The positive coefficient indicates that females are dropping out at a somewhat higher rate than expected given their social class and at-riskness behaviors. This result is consistent with findings from Ekstrom et al. (1986) indicating that females drop out for different reasons than males. Among the school-level controls, mean at-riskness has a

[4] Defining appropriate control or adjustment variables in research on school effects is a difficult problem. Ideally, we wish to adjust for differences among schools in the characteristics which the enrolled students bring to the school. In this way, we partition the observed differences among school outcomes into student and school effects. Obviously, measures of personal background, ability and prior school experiences fall into this category. Student attitudes and behavior while in high school are more problematic, however, in that these variables may actually be influenced by schools. Controlling for such variables would remove at least part of the school effect we seek to identify. Since our purpose was to explore possible school effects rather than offer a definitive test of a specific causal model, we adopted a middle-of-the-road strategy. We did not include ATRISK in modeling absenteeism because it was measured concurrent with LOGABSNT and as a result might reflect temporal idiosyncracies in addition to masking underlying school effects. As a result, the absenteeism analysis may have overestimated the school effects. By including it in the DROPOUT analyses, however, we may be underestimating the school effects since at least some of the components of ATRISK are likely to be affected by schools.

Table 7

Effect of Sector on School Dropout Rates,
Social Class and At-Riskness Differentiating Effects

School Effects	Variables	SECTOR added last Coefficient	Std. Error	% Δ R^2
Base Dropout Rate	BASE	.079	.008	
	SCHSES	-.004	.006	
	SCHATRSK	.058	.005	
	SECTOR	-.024	.012	7.7
Social Class Differentiation	BASE	-.030	.007	
	SECTOR	.026	.010	14.7
At-riskness Differentiation	BASE	.061	.006	
	SECTOR	-.034	.009	24.3
Adjusted for	ACADBKGD	.004	.004	
	BLACK	-.009	.015	
	HISPANIC	.001	.012	
	SEX	.017	.007	

strong positive relationship to dropout rates. When this variable is included in the model, the effects of school social class are negligible.

The results for a sector effects model are presented in Table 7. Since equation (10) is a simple linear probability model, the estimate β_{j0} coefficients are in a probability metric. The base dropout rate in the public sector is .079. In the Catholic sector, the base probability of dropping out is only .055 (i.e. $.079 + (-.024)$).

As expected, student social class is negatively related and at-riskness is positively related to dropping out. The differentiating effects in the public sector for social class and at-riskness are -.030 and .061 respectively. In the Catholic sector, these effects are -.004 (i.e.$-.030 + .026$) and .027 (i.e. $.061 + (-.034)$).

These results indicate that the social distribution of dropping out is more equalizing in the Catholic than public sector. Not only are base dropout rates lower in the Catholic sector, but these schools are also less differentiating environments. Social class is virtually unrelated to dropping out within Catholic schools, and the effects of at-riskness on dropping out is only half as large as in the public sector.

Effect of school-level factors. We posed separate HLMs for each of the five school-level factors. Seven control variables were included in each of these models. Student-level controls were introduced for academic background, sex, Black, and Hispanic group membership. Because a substantial proportion of the variance in the base dropout rates is accounted for by school social class and mean at-riskness (see Table 6), these two school-level variables were also included in the five models for the base rate.

Table 8 presents estimates of the best fitting models for each of the five school-level factors. The percentage of variance explained by each model are based on a comparison of the estimated residual variances for each model to the residual variance estimates from the model that only included the seven control variables (line 3 in Table 6). The difference between the two estimates is expressed as a proportion reduction in variance, $\%\triangle R^2$, relative to the model with only the control variables.

i. *Effect on base dropout rates.* The Curriculum and Composition factors are the strongest predictors of base school dropout rates, accounting respectively for 10.8 and 9.6 of the residual variance in the base rates. The Academic Press factor also contributes significantly ($\%\triangle R^2$= 5.4). The results for the base dropout rates are generally consistent with our initial hypotheses, and with the results reported above for absenteeism. Dropout rates are higher in schools where there is extensive differentiation in students' course taking (CURDVST coeff. = .035) and in the social class composition of the school (SDSES coeff. = .044). Dropout rates are lower in schools where students do more homework (AVHMRWRK coeff. = -.032), have positive attitudes toward getting good grades (AVGDEATT coeff. = -.017), and where enrollments in academic programs are greater (AVACDPGM coeff. = -.022).

The estimated effects for AUTHRTY and AVLACKAC, however run counter to our original hypotheses. Although the simple correlations reported in Table 1 are consistent with our a priori expectations, the effects estimated after adjusting for differences among schools in the types of students enrolled are not. Adjusted base dropout rates are actually higher in schools where students perceive discipline to be fair and effective (AUTHRTY coeff. = .046), and are lower in schools where students perceive a lack of academic emphasis (AVLACKAC coeff. = -.019).

ii. *Differentiating effects of social class.* Six individual school variables from four different factors are associated with social class differentiation. As hypothesized, there is greater differentiation in larger schools (SIZE coeff = -.018) and in schools with a high incidence of discipline problems (CLMFAC coeff. = -.014). Schools that emphasize academic pursuits, on the other hand, have more equalizing environments. A high level of enrollment in academic programs (AVACDPGM coeff. = .018), good student academic backgrounds (AVACBGD coeff. = .013), and a concentration on academic pursuits (ACADEMP coeff. = .013) all act to weaken the expected differentiating effects of social class.

Interestingly, there is no evidence of effects for school social class, average at-riskness, or minority concentration on social class differentiation. That is, the effect a student's social class on the probability of dropping out of school does not vary among schools with these different compositional features. The only unanticipated result was the disequalizing effect associated with students' perception of discipline as fair and effective (AUTHRTY coeff. = -.006). We had expected student social class to be less predictive of dropping out in schools where students perceive discipline to be fair and effective. In fact, the reverse is true.

Table 8

Comparison of Alternative Models for School Dropout Rates and the Differentiating Effects of Social Class and At-Riskness

			Base Dropout Rate	Differentiating Effects SES	ATRISK
School-level Factor		Variables	Coeff. (S.E.)	Coeff. (S.E.)	Coeff. (S.E.)
I	Teacher Quality	BASE	.068 (.005)	-.017 (.005)	.049 (.005)
		SCHSES	-.007 (.006)	...	...
		SCHATRSK	.059 (.005)	...	...
		STFPBLM	...	...	.014 (.005)
		PCDQLTCH	...	...	...
		$\%\Delta R^2$	.8	4.9	23.6
II	Academic Press	BASE	.060 (.005)	-.017 (.005)	.048 (.005)
		SCHSES	-.002 (.007)	...	...
		SCHATRSK	.047 (.005)	...	...
		AVLACKAC	-.019 (.007)	...	.019 (.006)
		AVHMEWRK	-.032 (.006)	...	...
		AVGDEATT	-.017 (.005)	...	...
		AVINTRA	...	...	...
		ACADEMP	...	.013 (.005)	...
		$\%\Delta R^2$	5.4	23.5	8.3
III	Disciplinary/ Social Climate	BASE	.074 (.005)	-.020 (.005)	.041 (.005)
		SCHSES	-.019 (.006)	...	...
		SCHATRSK	.071 (.005)	...	...
		AUTHRTY	.046 (.005)	-.006 (.004)	-.023 (.004)
		SCHSPIRIT	...	...	...
		CLMFAC	...	-.014 (.004)	...
		SAFE	-.008 (.006)	...	...
		$\%\Delta R^2$	.8	28.4	18.1
IV	Curriculum	BASE	.061 (.005)	-.019 (.005)	.045 (.005)
		SCHSES	.007 (.008)	...	...
		SCHATRSK	.046 (.005)	...	...
		AVMTHEMP	...	...	...
		SIZE	...	...	...
		CURDVST	.035 (.005)	...	...
		AVACDPGM	-.022 (.008)	.018 (.004)	-.013 (.004)
		$\%\Delta R^2$	10.8	28.4	16.0
V	Composition	BASE	.071 (.005)	-.029 (.006)	.041 (.005)
		SCHSES	-.015 (.006)	...	-.014 (.005)
		SCHATRSK	.054 (.005)	...	...
		SIZE	...	-.018 (.006)	...
		HIMNRTY	...	...	...
		SCHDRPRT	...	...	...
		SDSES	.044 (.005)	...	...
		SDATRSK	...	...	.016 (.005)
		AVACBGD	...	.013 (.004)	...
		$\%\Delta R^2$	9.6	15.7	25.0

(...) the t-ratio of coeff./S.E. is less than 1.5.

iii. *Differentiation effects of at-riskness.* The significant effects for at-riskness differentiation are consistent with our a priori expectations. Schools with high levels of staff problems(STFPBLM coeff. =.014), where students report weak academic expectations (AVLACKAC coeff. = .019), and where the diversity among students in at-risk behavior is great (SDATRSK coeff. =.016) are more differentiating environments. The at-risk student is more likely to drop out if enrolled in a school with one or more of these characteristics. The at-risk student is less likely to drop out if attending a school where students' perceive discipline to be fair and effective (AUTHRTY coeff. = -.023), and where a high percentage of students are enrolled in an academic program (AVACDPGM coeff. = -.013).

The only unanticipated result was the weaker at-riskness differentiation in higher social class schools (SCHSES coeff. = -.014). In these contexts, the at-risk student is less likely to drop out. Both the greater fiscal resources (and presumably greater programmatic resources for the at-risk student), and stronger norms about school completion in high SES schools are possible explanations for this result.

A composite model for dropping out. Table 9 presents the results a composite model of school effects on base dropout rates and differentiation effects with regard to social class and at-riskness. This model was developed using the same procedures that we employed in formulating the composite model for absenteeism. After the best fitting model was identified, the SECTOR variable was added and the model reestimated to determine the magnitude of remaining differences between the two sectors.

We focus first on the basic composite model (i.e. without the SECTOR variable). Base dropout rates are lower in schools where there is a high concentration of students in academic programs (AVACDPGM coeff. = -.030), where students report greater homework (AVHMEWRK coeff. = -.014) and where they feel safe (SAFE coeff. = -.015). A socially diverse school (SDSES coeff. = .027), where students pursue diverse courses of study (CURDVST coeff. = .033) have higher base dropout rates. One anomolous result persists - higher base rates are associated with schools where discipline is more likely to be perceived as fair and effective (AUTHRTY coeff. = .052).

In terms of social class differentiation, lower social class students are more likely to drop out if they are enrolled in big schools (SIZE coeff. = - .010), and in schools where discipline problems are prevalent (CLMFAC coeff. = -.009). These same students are less likely to drop out if attending a school where a high proportion of students are in an academic program (AVACDPGM coeff. =.020). The anomolous result for AUTHRTY persists here as well. There is greater social class differentiation in schools where discipline is perceived to be fair and effective (AUTHRTY coeff = -.016).

At-risk students encounter a greater likelihood of dropping out if they are enrolled in schools where principals report problems with staff (STFPBLM coeff. = .011). There is less at-riskness differentiation in high SES schools (SCHSES = -.007) and in schools where discipline is perceived to be fair and effective (AUTHRTY = -.019). The latter result is consistent with our a priori hypotheses, and runs counter to the results for base dropout

Table 9

A Composite Model for School Dropout Rates and the Differentiating Effects of Social Class and At-Riskness

School Effect	Variables	Model Coeff.	Model S.E.	SECTOR added last Coeff.	SECTOR added last S.E.
Base Dropout Rate	BASE	.067	.005	.082	.009
	SCHSES	.002	.008	.002	.008
	SDSES	.027	.006	.027	.006
	SCHATRSK	.042	.006	.043	.006
	AUTHRTY	.052	.005	.056	.005
	CURDVST	.033	.005	.031	.005
	AVACDPGM	-.030	.009	-.023	.010
	SAFE	-.015	.006	-.013	.006
	AVHMEWRK	-.014	.007	-.013	.007
	SECTOR			-.031	.014
	% Variance Explained		23.5		26.1
Social Class Differentiation	BASE	-.028	.006	-.032	.008
	AUTHRTY	-.016	.005	-.017	.005
	SIZE	-.010	.006	-.010	.006
	AVACDPGM	.020	.005	.018	.006
	CLMFAC	-.009	.005	-.009	.005
	SECTOR			.007	.014
	% Variance Explained		43.1		42.2
At-Riskness Differentiation	BASE	.044	.005	.042	.007
	AUTHRTY	-.019	.004	-.020	.005
	SCHSES	-.007	.005	-.008	.005
	STFPBLM	.010	.005	.011	.005
	SECTOR			.005	.012
	% Variance Explained		36.8		36.1
Student-level Controls					
	ACADBKGD	.003	.004	.003	.004
	HISPANIC	-.003	.012	-.003	.012
	BLACK	-.012	.015	-.014	.015
	SEX	.022	.007	.023	.007

rates and social class differentiation. That is, greater adult authority is associated with higher base dropout rates and more differentiation with regard to social class, but adult authority differentiates less with regard to at-riskness.

This composite model accounts for a substantial proportion of the variance in each of the three school effects. Relative to our base model that included the seven control variables, the composite accounted for 23.5% of the variance in base dropout rates, 43.1% of the variance in social class differentiation, and 36.8% of the variance with regard to at-riskness differentiation.

i. *Compositional effects.* The average background of students within a school can have an effect on individual student outcomes which is quite distinct from the effects of an individual's background on that outcome. Within HLM, compositional effects are represented in two different ways depending upon how the individual effect is modeled. First, in the case of academic background and race/ethnicity variables, where the individual-level β_{jk} coefficients are treated as fixed or constant across schools and the individual variables are centered around the grand mean as in equation 9, a compositional effect on dropping out is present when the school mean for the variable enters significantly in the between-school model for β_{j0}, the adjusted base dropout rate. Our analyses provided no evidence of compositional effects for either academic background or minority concentration.

Second, when the effect of the individual characteristic varies among schools, as in the case of social class and at-riskness, and these variables are centered around their respective school means, then the compositional effect is the difference between the estimated γ coefficient for the school aggregate in the between-school model for β_{j0} and the "BASE" estimate from the within-school model for that effect. In particular, the compositional effect for at-riskness is simply the difference between the effect of SCHATRSK in the model for the dropout rate and the BASE estimate in the at-riskness differentiation model. From Table 9, we see that this compositional effect is $(.042 - .044. =) - .002$. Thus, there is also no evidence of a compositional effect for at-riskness. There is, however, an indication of compositional effects for social class (effect = .030). The dropout rate in high SES schools is considerably higher than we would expect given the favorable characteristics of the students enrolled and features of these schools. This result points toward the problem of the "middle class" dropout (Coleman & Hoffer, 1987) where the traditional explanations for student alienation - weak school programs, family and communal poverty, and a deficient academic background - appear less compelling.

ii. *Contextual effects.* There is also considerable interest among researchers in contextual or *frog-pond* effects where an individual's performance on some outcome is conditioned by the student's relative standing within the school. Within HLM, contextual effects are represented by the inclusion of school aggregate measures in the between-school models for differentiating effects. The results in Tables 8 and 9 provide no indication of frog-pond effects. Neither school SES nor mean at-riskness enter for their respective differentiating effects.

Results for the sector effects model. As a final test of the explanatory power

Table 10

Organizational Correlates of School Size

	Bigger Schools are more likely to have:	Correlation
1.	greater faculty resources (FACRES)[1]	.433
2.	greater incidence of staff problems as perceived by principals, e.g. absenteeism and lack of interest (STFPBLM)	.481
3.	greater incidence of student discipline problems (CLMFAC)	.394
4.	more tracking (TRKDVST)[2]	.353

[1] FACRES is a school-level factor composite of % of teachers with advanced degrees, % with more than 10 years, first step on salary scale, and % turnover in the last year.

[2] TRKDVST is a measure of the proportional allocation of students across the academic, P_A, the general, P_G, and vocational tracks, P_V. Formally, $TRKDVST = P_A(1 - P_A) + P_G(1 - P_G) + P_V(1 - P_V)$. TRKDVST takes on a maximum when students are equally dispersed among the three tracks and a minimum (0) when students are all concentrated in a single track.

of the composite model, the SECTOR variable was reintroduced into each of the three between-school equations. Recall that our goal was to construct a model that accounted for the sector differences reported in Table 7, since such a model would add credibility to the claim that the specific school-level variables included in the final model are causally linked to student outcomes. In this regard, we were only partially successful. We are able to account for the weaker diffferentiating effects of both social class and at-riskness in the Catholic sector in terms of specific school variables (Table 9). The estimated SECTOR effect in each case is considerably less than one standard error. The base rate differences, however persist (SECTOR coeff. = -.031) even though a number of school-level variables have been identified which are associated with differences among schools in base dropout rates.

A special note on the effects of school size. As we noted earlier, school size (SIZE) was considered as part of both the Curriculum Structure and Composition factors. With the exception of a role in modeling differentiation effects of dropping out with regard to social class, we encountered relatively little evidence of direct effects of this structural feature on either absenteeism or dropping out. This should not be interpreted, however, as indicating that school size is of little consequence. Absenteeism and dropout rates are higher in larger schools. The simple correlation between school size and absenteeism is .20, and with dropout rates, .14. Our analyses suggest that school size may be an important moderating variable. Organizational correlates of school size (see Table 10) indicate that larger schools are more problematic social environments for both students and teachers. Although such schools have greater faculty resources in terms of teachers with more experience, with more advanced degrees and where starting salaries are higher, principals are also more likely to report a greater incidence of staff absenteeism and lack of interest. Student discipline problems are greater in such schools and their is greater internal academic differentiation through tracking. The correlations reported in Table 10 are among the largest we encountered in examining bivariate relationships among school-level variables. This suggests that the effects of school size are in fact substantial, but mostly indirect acting to either facilitate (in small schools) or inhibit (in larger schools) the development and maintenance of a social environment conducive to student and faculty engagement with the school.

Discussion

Summary of Results

We hypothesized that high levels of internal differentiation within high schools and weak normative environments contribute to the problems of absenteeism and dropping out. Conversely, these student behaviors should be less problematic in school contexts where there is less differentiation among students and strong normation.

The empirical results reported in this paper support these hypotheses. Absenteeism is less prevalent in schools where faculty are interested and engaged with students, and there is an emphasis on academic pursuits. An orderly social environment is an important condition. Absenteeism is also lower in schools where there is less internal differentiation in term of the characteristics that students bring to the school and how schools in turn structure academic programs in response to the differences among the students they enroll. We encounter similar findings for base dropout rates. Students are more likely to persist to graduation in schools where there is an emphasis on academic pursuits, an orderly environment, and less internal differentiation.

The analyses also provide some support for the contention that special benefits accrue to disadvantaged and at-risk youth from attending certain kinds of schools. A committed faculty, an orderly environment, and a school emphasis on academic pursuits are all associated with lower probability of dropping out for such youth. An important structural feature - a smaller school size - also contributes to engaging the disadvantaged student. The greater opportunity to sustain informal face-to-face adult-student interactions in such contexts would seem to provide a compelling explanation for these results (see McDill et al., 1986).

The single unexpected result is the pattern of associations with the adult authority variable which is only partially consistent with the hypothesis articulated by Wehlage and Rutter (1986). Student attendance is better in schools where the exercise of adult authority is perceived by students to be fairer and more effective. The fair and effective exercise of adult authority also appears to benefit at-risk youth. A prompt, effective adult response to student behavior problems early in high school may short circuit what otherwise might be a continuous flow of negative school experiences culminating in a decision to drop out. On the other hand, fair and effective discipline is also associated with higher base dropout rates and more disequalizing effects with regard to social class. While it is possible to construct a posthoc rationale for these results, we prefer to leave them simply as noted but uninterpreted.

In general, the findings presented in this paper tend to support a school ethos explanation as first articulated by Rutter et al. (1979). No single factor makes schools effective in sustaining student interest and commitment. Rather, a constellation of both structural and normative features appears to be involved. Taken together, these factors create environments which jointly engage both faculty and students in a common round of social life that is apparently of considerable meaning to both.

Possible unidentified selection artifacts. Important causal questions of course still remain. No matter how sophisticated the analysis or how extensive the list of confounding variables considered, there is always some possibility that the estimated school effects are more a function of the kinds of students enrolled than the organizational characteristics of the schools. Thus, an alternative explanation for our results is that the school variables employed in our analyses are simply proxies for other unidentified differences among the students enrolled in the various schools. It might be argued that schools with lower dropout rates are able to sustain their particular organizational characteristics because of the preferrable student populations that they serve. In response to this concern, we introduced explicit controls in our analyses for several student background characteristics that have been demonstrated in prior research to be predictors of dropping out and absenteeism.

Concerns about unidentified selection artifacts would appear most salient as an alternative explanation for mean differences across schools on absenteeism and dropping out (i.e. the base dropout rates). But the HLM analyses for dropping out also indicate school organization effects on internal differentiation with regard to social class and at-riskness. Although this too could be a selection artifact, a more contorted explanation is required since the estimated differentiation effects are interactions between student characteristics and specific organizational variables. Why residual selection effects should appear in this form is unclear. Further, the fact that the school variables introduced in the analyses explain away the observed sector differences on mean absenteeism and the differentiating effects of social class and at-riskness adds credibility to the school organization explanation.

In most general terms, even if unmeasured student-level confounding variables exist, the consequence is more problematic for interpreting the effects of the other student-level variables than for the school effects. The reason for this is as follows: Suppose there is an unmeasured student-level confounding variable, X_{ijk}. For it to influence the estimated effect of a school organizational variable, Z, there must be a covariation between the school mean on the confounding variable, $X_{.jk}$, and Z. Further, for the effect of the school organizational variable to change when the additional student-level covariates is entered in the model, $X_{.jk}$ must have an independent relationship with Z, above and beyond the effects of the measured $X_{.j}$'s already included in the model. That is, the partial regression coefficient of Z on $X_{.jk}$ controlling for the other $X_{.j}$'s must be nonzero. Because of the sociological processes by which students are assigned to schools, however, the intercorrelations among school means are usually substantially larger than the correlations among the correponding student-level variables. As a result, the likelihood that some unmeasured $X_{.jk}$ has a substantial orthogonal relationship to Z, after controlling for a set of other $X_{.j}$ is small. Stated somewhat differently, the set of student-level controls included within an HLM can act as instrumental variables (Johnston, 1972) for purposes of estimating the effects of specific organizational variables. This means that although it may be inappropriate to consider the estimated student-level effects as structural coefficients, such an interpretation for the school-level variables may be quite appropriate.

Unexplained sector differences on base dropout rate. In the final composite model, the base dropout rate in the Catholic sector remains 35 percent lower than in the public sector. There are two sources of explanation for this. The first is residual selection artifacts already discussed above. The second source of an explanation is other school characteristics not considered in our analyses. In general, the measures of school normative environment from HS&B are rather weak because the core data does not include information from teachers.[5] As a result, the content of teacher beliefs and degree of consensus among school faculties on such issues remain unmeasured. Other possible sources of explanation are organizational differences that result from governance and other school policies. Recent research (Chubb & Moe, 1988) has demonstrated substantial differences between sectors in this regard. The involvment of parents and their support for the school is another area that merits examination.

Concluding Comment

In closing, the research reported here is another strand in a growing web of investigations which support the conclusion that the internal organizational features of schools can have significant educative consequences for all students, and especially at-risk youth. A picture emerges from our analyses of a distinctive organizational environment that appears particularly effective. These are smaller high schools where there are substantial opportunities for informal adult-student interactions, where teachers are committed and interested in working with students, and where students are pursuing similar courses of academic study within an environment that is safe and orderly. These are institutions whose structure and functioning coalesce around a sense of shared purpose. The result is a coherent school life that is apparently able to sustain the engagement of both students and teachers alike. Such strongly chartered schools (Meyer, 1970) appear our best hope in response to problems of individual alienation.

[5]The recently released supplement to HS&B, *The Teacher and Administrator Survey* (1988), provides supplemental data on a subsample of HS&B schools which substantially extends the range of school variables that can be constructed. Although there are some potential difficulties in the use of these data in conjunction with the HS&B base files, because the supplement was collected almost two years after the base data, they still merit further examination.

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TECHNICAL APPENDIX: HLM ESTIMATION

For each sample of n_j students in school j, $j = 1, 2, ..., N$, we specify a *student-level* or *within-school* model for the outcome variable, y_j,

$$y_j = X_j\beta_j + \varepsilon_j \ . \qquad (A.1)$$

y_j is an $n_j \times 1$ vector of observations in school j, X_j is the $n_j \times p$ matrix of within-school predictors, and β_j is the $p \times 1$ vector of regression coefficients. As for the usual multiple regression model, the $n_j \times 1$ vector of random errors within school j, ε_j, is assumed to be normally distributed as

$$\varepsilon_j \sim \mathcal{N}(0, \sigma^2\mathrm{I}) \ ,$$

and are independent of the predictors in the model.

We next assume that these student-level relationships, as captured by the within-school regression in $(A.1)$, vary across schools. In particular, we consider the vector of regression coefficients for school j, β_j, random and, given a $1 \times q$ row vector of school- level predictors, z_j', it is represented by the multivariate regression model,

$$\beta_j = Z_j\gamma + v_j \ . \qquad (A.2)$$

To permit a more flexible model to be specified, Z_j is a block- diagonal matrix with p blocks of the row vector, z_j', or a sub- vector of it. The vector of regression coeffcients, γ, in $(A.2)$ is thus a column vector of the appropriate dimension. As with a multivariate regression model, the residual parameter variance, v_j, is assumed to be multinormally distributed with a null mean vector and variance-covariance matrix Υ, or

$$v_j \sim \mathcal{N}(0, \Upsilon) \ .$$

Estimates for β_j, the regression effects in school j, can be obtained by the ordinary least squares (OLS),

$$\hat{\beta}_j = (X_j'X_j)^{-1}X_j'y_j \ . \qquad (A.3)$$

The sampling variance of $\hat{\beta}_j$ is

$$Var(\hat{\beta}_j|\beta_j) = V_j = \sigma^2(X_j'X_j)^{-1} \ . \qquad (A.4)$$

Given that β_j has a distribution in the population of schools, as specified by $(A.2)$, the total dispersion in the $\hat{\beta}_j$ is

$$Var(\hat{\beta}_j) = Var(\hat{\beta}_j|\beta_j) + Var(\beta_j) = V_j + \Upsilon \ . \qquad (A.5)$$

This reasoning leads to the following generalized least squares (GLS) estimator for the school-level regression coefficients:

$$\gamma^* = \left[\sum_j Z_j'(V_j + \Upsilon)^{-1} Z_j\right]^{-1} \sum_j Z_j'(V_j + \Upsilon)^{-1} \hat{\beta}_j \,. \tag{A.6}$$

Equation ($A.6$) can be viewed as an application of weighted least squares where the contribution of each school to γ^* are inversely proportional to the variability associated with that estimate.

If the variance components σ^2 and Υ are known, equation ($A.6$) provides a means for estimating the γ^* parameters in the HLM model. In most applications, however, both σ^2 and Υ must be estimated from available data. It can been shown that, under quite general conditions, the EM algorithm (Dempster, Laird, & Rubin, 1977) can be used to provide maximum likelihood estimates, $\hat{\sigma}^2$ and $\hat{\Upsilon}$, for the variance components, σ^2 and Υ, respectively. These estimates are asymptotically unbiased, consistent, efficient, and are asymptotically normal. In most applications, they are substituted into ($A.6$) for their parameter values, and the γ^* are estimated in turn conditional on these estimated variance components. For further details of the EM estimation in the HLM context, see Raudenbush (1988).