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ABSTRACT

Hierarchical linear modeling allowed the indentification of specific school characteristics and policies which help explain the relationship between social class and minority status with mathematics achievement, the relationship between social class and minority status with mathematics course enrollment, and school means for achievement and for course enrollment. Major explanatory variables which emerged from the present analyses as predictors of all of the relationships of interest, fall into a small number of categories. Results indicated that there are considerable differences between Catholic and public schools on these outcomes, differences which favor Catholic schools. These analyses show that three sets of factors can effectively explain those cross-sector differences: (1) variation in the social content of schools; (2) variation in the academic and disciplinary climate among schools; and (3) variation in curricular offerings and requirements. Previous research results concluded that Catholic schools induce consistently higher mean achievement and that mean course enrollment in their students must be somewhat refined. The Catholic schools' advantage in mean school mathematics achievement and the more equitable distribution of that achievement appears to be explainable by the described school-related factors. It was concluded that Catholic sector advantages are explainable by a reasonably modest set of school characteristics and policies. References, tables and figures are provided. An appendix shows the computer output from the hierarchical linear modeling program. (PN)

Multi-Level Causal Models for Social Class and Achievement

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BACKGROUND

Social Class and Academic Achievement.

Ideally, the institution of schooling should encourage academic progress in students regardless of their family background or their race or ethnicity. However, the positive relationship between social class (SES) and academic achievement, exemplified by the correlation between these two factors, has been well documented. White (1982) summarized over 200 studies which examine this question. At the student level, White found the average relationship between SES and achievement to be .22, but the same relationship using data aggregated to the school level jumped to .73. The higher relationship among schools than students is chiefly a statistical artifact of aggregation.

Several researchers have shown that this relationship is less strong among students who attend Catholic secondary schools than their counterparts in public schools (Coleman, Hoffer & Kilgore, 1982; Hoffer, Greeley & Coleman, 1985; Lee, 1985). This finding forms the basis of Coleman et al.'s often cited claim that today's Catholic schools more closely resemble the traditional American concept of "the common school" than do contemporary schools in the public sector. Corresponding analyses which compare the relationship between minority group status and academic achievement in the two school sectors have similarly found a weaker relationship among Catholic than public high school students (Greeley, 1982; Keith & Page, 1985; Lee, 1985).

Although the fact that Catholic high schools seem to induce high academic outcomes among a broader social and racial distribution of students is an interesting phenomenon in itself, by far the more compelling educational puzzle involves discovering exactly why this seems to be the case. Precisely what it is about the characteristics and practices of schools in the Catholic sector which enables them to foster academic achievement in a manner which is relatively unrelated to the social stratification of their students? Of course, investigation of this question falls into a broader category of educational inquiry which could be summarized by asking, "How do schools affect their students?" A new method to answer this type of question is explored in this paper, and a specific investigation of some characteristics and practices of Catholic and public schools which relate to sector differences in the social distribution of academic achievement is undertaken.

The Hierarchical Nature of School Research.

How schooling effects students is by definition a multilevel question. Researchers have been critical of educational research which draws conclusions about the effects of specific pedagogical programs on the basis of aggregated, rather than individual data (Haney, 1980; Burstein, 1978; Murnane, 1985; Burstein and Miller, 1981). These researchers suggest that in most cases the individual student is the appropriate analytic unit for study of educational processes and programs, since it is change in individuals to which such processes and programs are directed. In fact, inducing individual change is quite ingrained in the American cultural philosophy, according to Daniel Bell. He writes: "The principle of equality of opportunity derives from a fundamental tenet of classic liberalism: that the individual -- and not the family, the community, or the state -- is the basic unit of society" (Bell, 1972:29). However, there are certainly instances in which study of groups (especially schools or classrooms) is both logical and appropriate.

Regardless of the theoretical reason for selecting one or another unit for analytic focus in educational research, it is seldom the case that grouped and ungrouped estimates of the same parameter are equal. For example, the effect of average social class on average achievement was shown by White (1982) to be much stronger than the same relationship at the individual level. In fact, Burstein (1978) suggests four separate tests to determine whether aggregated results produce biased estimates of individual effects, and comes to the conclusion that only under very specific (and unlikely) circumstances can aggregated results be considered unbiased (See Note 1). Additionally, these difficulties are much more serious when they are applied to non-experimental or naturalistic studies where assignment to groups has not been made at random. The nature of educational treatment and research is very largely non-experimental. The High School and Beyond (HS&B) study represents an especially fine example of such non-experimental educational data. Yet its non-experimental nature makes either aggregation or disaggregation problematic for studying cross-unit processes.

Clearly, to present an accurate conceptual picture of the particular nature of the schooling process being addressed in this paper, recognition of the fact that students experience schooling in groups is essential. Methodologically and substantively, such recognition requires accounting for the fact that students within the same school are not independent of one another, and that most educational relationships have both within-school and between-s hool components. An adequate representation of the schooling process can be constructed only by considering its hierarchical nature. However, such considerations present both conceptual and methodological difficulties to researchers. Burstein and Miller believe that "...the major technical complication in the analysis of multilevel data from quasi-experiments...is the inability of educational researchers to develop adequate...methodology for analyzing the educational effects of [educational] processes [within groups]" (Burstein and Miller, 1981:195)

Constructing meaningful conceptual models about the process of schooling is therefore more complicated than simpling choosing either student, classroom, or school as the analytic unit. Important phenomena take place at all three levels, in what is essentially a hierarchical structure -- especially, students nested within schools. Therefore, we are faced with a two-level hierarachical model: students grouped in schools.

The critical problem with this sort of model, according to Burstein and Miller (1981), "is that educational treatments are not administered independently to individuals" (p. 204). This non-independence they call "interclass correlation." Until recently, research had been restricted to considering either between-student or between-school data, the latter often consisting of both school-level variables (school size, per-pupil expenditure, student-teacher ratios, or specific school rules, for example) and aggregates of student-level variables (e.g. school mean achievement, average time spent on homework, or mean number of math courses taken). The difficulty of such single-level research is that it reqires one of two assumptions. At the student level, the assumption is that the interclass correlation is zero (i.e. that students react to an educational treatment completely independent of one another). On the other hand, school-level analysis assumes that the interclass correlation is total, that treatment is identical for all students in the school. Neither assumption is plausible.

This presents researchers with a particularly difficult problem: combining more than one unit nto a single analysis. Some studies have included aggregates of student data (e.g. the average SES of students in a particular school or the percent minority enrollment of the student body) in student-level analysis (Alexander, McDill, Fennesy & D'Amico 1979; Bryk, Holland, Lee & Carriedo 1984; Hoffer et al., 1985; Willms, 1984). This approach has been both encouraging and somewhat disappointing. It is encouraging that researchers have begun to consider within-group, or contextual, effects on individual outcomes. It seems logical that different combinations of institutional practices in schools result in varying distributions of educational outcomes for students with similar background characteristics. This sort of research is directed at assessing the effects of school-wide practices and descriptive characteristics on individual students within those schools. However, research results have generally found such school-level effects to be weak, particularly when compared to the disaggregated version of the same variables. Alexander et al. (1979) conclude that average social class is not a strong contextual determinant of educational aspirations in comparison to individual SES. Bryk et al. (1984) found school social class to be weaker than student SES in predicting achievement at sophomore and senior year. Recall that Coleman, Campbell, Hobson, McPartland, Mood, Weinfeld & York (1966) and Jencks, Smith, Acland, Bane, Cohen, Gintis, Heyns & Michelson (1972) reported essentially the same phenomenon in their landmark studies on equal educational opportunity.

Besides evaluating the effects of specific school institutional characteristics and practices on mean student performance, some researchers have suggested that specific relationships within schools be considered as dependent variables in school-level analyses. An example of such a research question, in fact the one addressed in this paper, might be phrased as follows: "What is the effect of differences in specific curriculum policies, context, or school climate between schools on the relationship between social class and academic achievement within each school?" Such a question requires a reconceptualization of school outcomes, traditionally seen as means of indivdual behaviors, into consideration of within-school regression coefficients as dependent variables in between-school models. Although Burstein and Miller (1981) suggest consideration of the slopes-as-outcomes concept, they point out certain methodological difficulties in this approach. The major difficulty of this interesting concept is that estimation of regression slopes is often done with a great deal of error, particularly if within-school group sample sizes are small. There is considerably more error involved in estimating group regression slopes than group means. The difficulty in using these slopes as outcomes of school-level analyses is being able to separate the variation in the slope into its "real" and "random error" components -- yet another example of the classic statistical problem of distinguishing "signal from noise."

Although many educational researchers have recognized the need for multilevel analysis of educational research, they have often issued cautionary statements about the methodological difficulties involved. However, there are several statisticans who have addressed these difficulties (especially Lindley and Smith, 1972; Mason, Wong and Entwisle, 1984). Mason et al. (1984) detail the statistical models for a two-stage process. In these models, the first stage (the micro model) is a linear equation within each unit in which a vector of predictor variables is regressed on a single outcome. The regression coefficients from the micro model, including the intercept term or regression constant, become dependent variables in the second stage, or macro model. The macro model is a series of equations on that set of regression coefficients between units. The vector of independent variables in the macro model are group-level predictors. Certain distributional assumptions are made about these models, particularly that the error terms are both independent and normally distributed both between and within contexts (i.e. groups). In order to estimate the parameters of these models at both the micro and macro levels, these researchers recommend using restricted maximum likelihood estimation procedures, which employ a Bayesian approach (See Note 2). The advantage of the restricted maximum likelihood estimation procedure is that the estimates of error variance are generally smaller than with OLS regression, even two-stage least squares.

Hierarchical Linear Modeling. Raudenbush and Bryk (1986) have detailed the slopes-as-outcomes approach for the analysis of educational described above in a procedure they call hierarchical linear modeling (HLM). it is their exact methodology (including their HLM program) which has been employed for the analysis in this paper. Although their paper is primarily a methodological exposition of the hierarchical approach to analysis of the effects of schools on students, they have chosen as a descriptive example of the procedure a re-analysis of Coleman et al.'s 1982 exploration of the "common school effect." Although they do not challenge Coleman's conclusions, they speculate on the potentially spurious results which can result from single-unit analysis, since the potential effects of the school as a sociological unit were ignored in Coleman et al.'s analyses.

Prior research which attempted the two-stage approach implied by slopes-as-outcomes methodology has not been free of difficulties, according to Raudenbush and Bryk. The primary difficulty, as stated above, is the greater variability in the estimation of regression coefficients than of sample means. The error variance of slopes is further increased if the variation in the first stage between the two variables for which the slope is to be computed (e.g. achievement and SES) is constrained within units. It is highly probable that individual schools are more homogeneous with respect to SES, for example. If the sampling precision for slopes varies across units, also highly probable in school research, the basic assumption of OLS of homogeneity of variance has been violated. In fact, the variability in slopes should be divided into two components -- variance of the parameter itself and variance due to sampling error. The essence of the hierarchical linear modeling procedure involves partitioning that variance of first-stage regression slopes into its parameter and sampling components, and estimating only the parameter variance as accurately as possible. This allows the effects of second-stage (school-level) predictors of those slopes to be more accurately estimated than in previous research using this approach. Generally, this means that school effects will be larger.

The estimation of first stage (i.e. within-school) regression coefficients with reduced error variance is accomplished by using a Bayesian estimation procedure which weights the estimate of the regression slope by its "reliability." The reliability coefficients, or weights, are computed by comparing the initial estimates of the slope for each school to the estimate of the mean slope across all schools. If the initial estimate of the slope is less reliable, it is weighted down and the group slope is weighted more. This procedure, called Empirical Bayes estimation, is an iterative process using the EM algorithm explained by Dempster, Laird, and Rubin (1977) and based on Lindley and Smith's seminal work. Using maximum likelihood estimation (MLE) methods to compute variances for these slopes, successively smaller MLE's of variances are entered into estimation equations until convergence is reached. The advantage of this procedure lies in the reduction of variance of the estimates of regression slopes (and intercept), maximizing whatever information is available.

The procedure allows the use of statistical inference in significance testing of parameter estimates, for both the first- (within-school) and second-stage (between-school) models. Since regression slopes are estimated more accurately than in previous expositions of this approach, estimates of the effects of school-level variables on these slopes will usually be stronger than those found in previous work. Although this methodology appears to be ideally suited to the question addressed by this paper, there are certain limitations to its application. Under ordinary circumstances, it is necessary to have adequate sample sizes at both stages. However, a recent program development allows users to produce robust analyses of regression coefficients for each school even if sample sizes are somewhat limited within each school, using a mixed-model approach with additional Bayesian estimation procedures (Braun, Jones, Rubin & Thayer, 1983). The second stage analyses require that a sufficient number of schools are sampled. In fact, in the analyses for this paper which use data from HS&B, adequate data are provided at both stages, since up to 72 students were sampled in each of over 1,000 schools. Under such sampling procedures, within-school regressions will be considerably simpler (i.e. use fewer independent variables) than those between schools.

METHOD

Sample and Data

The sample used for HLM analyses in this paper is drawn from both the base-year (1980) and first follow-up (1982) from High School and Beyond. The sample includes all Catholic high schools (n=83) and a random sample of public high schools (n=77), for a total sample of 160 schools. The student-level sample employs the entire set of students selected in the base year of HS&B -- i.e. both sophomores and seniors in that year. This sampling plan was selected to maximize the within-school sample size, in order to produce maximally robust estimates of the slopes and intercepts which comprise first-stage parameters. Since it is important to have equivalent achievement and other information on students who were not equivalent at the time they were originally sampled, I have used achievement and course-enrollment information on all students at their senior year. This means that for 1980 sophomores that data came from 1982 follow-up information, whereas for 1980 seniors the relevant data were gathered at the base year. Background data (i.e. minority status, SES, and academic background) were those supplied by students at the base year. Math achievement test scores were equated to the same scale by using IRT (item response theory) scaling, the same procedure used by Hilton, Rock, Ekstrom, Goertz, and Pollack (1984) in their comparison of 1980 seniors from HS&B with 1972 seniors from NLS (National Longitudinal Study). Therefore, math achievement information is on a slightly different (but highly correlated) scale from other research which uses the HS&B math tests (See Note 3).

The HLM Program

Hierarchical linear modeling analysis proceeds in three steps. At the first step, the program reads the raw data at both the student- and school-levels, with school identification number as the cross-referencing variable. A matrix of sums of squares and cross products for each school is computed, along with the means and variances for each variable for students in that school. Attached to that matrix are the values for each school-level variable. Users have the option of listwise or pairwise deletion of missing data for the cross-product matrix. Pairwise deletion of missing data was selected for these analyses in order to maximize the sample size for each computation. With pairwise deletion, a matrix of sample sizes is attached to the other data for each school. The program writes out a matrix which contains the data just described for each of the 160 schools: student-level means and standard deviations, the cross-product matrix, a matrix of sample sizes used for the pairwise computations, and values of school-level variables. Users have the option of selecting which student- and school-level variables they would like to include in these matrices.

For schools where there is missing data on selected first-stage variables, the mixed-model method of constructing these matrices may be selected, using a Bayesian estimation method. Schools for which there is no variation in selected first-stage variables are dropped from the analysis. For example, in these analyses I have selected minority status (either black or Hispanic) as a within-school factor. However, there are some schools in HS&B which have very few or no minority students, and others which enroll only minority students. Since there is virtually no variation on minority status for those schools, a regression coefficient for minority status on math achievement cannot be estimated for that school, which results in that "case" being eliminated. The specific reason is that the variance-covariance matrix cannot be inverted for such a school, since it is not of full rank.

The second step of the HLM program includes the computation of actual within-unit parameter estimates. The program reads in the entire cross-product matrix just described, and computes MLE estimates from that matrix, using an iterative procedure. In this way, the considerable computer time necessary to compute the matrix is not duplicated for every model variation. Users have the option of specifying the number of iterations desired. Almost all computations for this paper have used five iterations, as it was found that convergance was very close at that point. In any single HLM run, users specify a set of first- and second-stage variables. In its current form, the program is limited to six independent variables for within-unit regressions at the first stage. Since HS&B sample sizes within schools range from about 40 to 72 cases (average: 62), this limitation does not constrain analyses for these data.

In the third step of the HLM procedure, the outputs from the first stage regressions (called "beta-hat's") become the dependent variables in the second stage analyses: a vector of means (intercepts) and vectors of slopes of each within-school predictor on the dependent variable. Within the same HLM run, users are able to specify which second-stage variables should be regressed on each of the first-stage outputs: means and slopes. In its current version, the program is limited to six second-stage predictors. However, users may specify different models for each of the second-stage dependent variables. Users have the option of requesting many different pieces of information in the computer output: the slopes and intercepts for each school (the beta-hat's), successive estimates of the second-stage parameters from each iteration (called "gamma-hat's"), and estimates of the variance matrices (called "V" for the error variance and "tau" for the parameter variance).

There are two essential components of the HLM program's computer output: (1) a table of gamma (*) estimates (the final second-stage parameters) with their standard errors, test (Z) statistics, and significance levels; and (2) a table of estimated paramater variances for each of the first-stage output variables (an intercept and one or more slopes), along with their degrees of freedom, test statistic (X^2), and significance level of each variance. By comparing these estimated parameter variances for first-stage outputs in different second-stage models, it is possible to compute what amounts to a change in variance explained (R^2) for a group of second-stage variables. This is equivalent to describing the amount of variance on a particular within-school paramet r that is explained by between-school factors.

Analytic Models

The analyses for this paper employ two first-stage models. The first has minority status (coded '1' for minorities, '0' for whites, called MNRTY80), social class (called SES), and academic background (ACDBKGD) regressed on math achievement (called IRTMATH, or BASE) (See Note 4). The second within-school model employs the sum of years academic math completed by students (Algebra I, Geometry, Algebra II, Trigonometry, Calculus) as the dependent variable (MATHEMPH), with the same independent variables: minority status, SES, and academic background. For both first-stage models, second-stage models were constructed to systematically search for school variables which have a significant effect on either the intercepts or slopes from first stage models. The intercepts, the minority-slopes, and and SES-slopes for achievement and course-taking are the first-stage parameters of special interest. The set of second-stage models were slightly altered for the two first-stage models. That is, analyses investigated the effect of several school-level factors on both intercepts and slopes.

The two-stage models used for HLM illustrate the general estimation procedure. A typical first-stage (i.e. individual regressions between students within each school in the sample) is the following:

Math Achievement	=	Minority Status	+	Social Class	+	Academic Background	(Model 1)

This model will provide estimates of four parameters for each school, each of which will be adjusted for all other independent variables in the model: (1) mean math achievement (call it 'Base'); (2) a regression slope of minority status on math achievement (Slope 1); (3) a regression slope of SES on math achievement (Slope 2); and (4) a regression slope of academic background on math achievement (Slope 3). These parameter estimates, which describe the relationships within each school, vary considerably <u>across</u> schools. In order to estimate the second-stage HLM parameters (equivalent to regression coefficients for school variables), the program uses the first-stage parameters as dependent measures, with independent variables which measure school descriptive and composition characteristics. A representative set of second-stage models might be the following:

Base A = Sector + Average SES + % Minority Enrollment (Model 2)

Slope 1 = Sector + Average SES + % Minority Enrollment (Model 3)

Slope 2 = Sector + Average SES + % Minority Enrollment (Model 4)

Slope 3 = Sector + Average SES + % Minority Enrollment (Model 5)

Results from Models 2, 3, 4, and 5 provide school-level parameter estimates of the effect of sector, average social class, and percent minority enrollment in the school on each of the within-school parameters. Although it seems advisable to adjust first-stage estimates for academic background, I have chosen not to discuss the slope of academic background on achievement in this paper. Model 2 answers the question, "Which school characteristics predict average math achievement?" Model 4 provides information on the following question: "Which school characteristics predict the relationship between social class and achievement across schools?" Although the same school-level models have been selected for the four within-school outcomes for ease of illustration, there is no constrait within the program on using different second-stage variables in Models 2 through 5.

In substantive terms which relate to the questions addressed in this paper, ideal second-stage variables would evidence the following characteristics:

- They would show a strong and positive relationship to average achievement (i.e. for Base A);
- They would show a positive relationship with Slope 1. That is, such variables would relate positively to the relationship between minority status and achievement, adjusted for SES differences,
- They would show a negative relationship with Slope 2. That is, these variables would relate to a lower slope between SES and achievement, which would be more equalizing. Note that the SES relationship has been adjusted for minority status (Note 5).

The overall purpose of this paper is two-fold. First, it is meant to demonstrate use of this program on an example of the sort of school effects question which can best be addressed using HLM methodology. To satisfy this first purpose of demonstrating use of the program, models have been kept reasonably simple. However, the second purpose of the paper is to investigate how HLM multi-level causal modeling methods can answer the specific question of why Catholic schools seem to be more socially equalizing in the distribution of academic outcomes than public secondary schools. To satisfy this second purpose, many different models have been investigated, and model formation has been more complex. In general, the analytic approach has involved the following successive but separate analyses as second-stage models :

(a) No second-stage variables (the unconditional model);
(b) Catholic school sector, coded '1' for Catholic schools, '0' for public schools (called SECTOR);
(c) SECTOR and average school social class, aggregated from the student-level SES variable in each school (called AVSES);
(d) SECTOR, AVSES, and a variable which separated schools with high-minority enrollment (called HIMTYSCL--see Note 6);
(e) SECTOR, AVSES, HIMTYSCL, and a the number of math courses offered in the school (called MATHOFF);
(f) Other combinations of school-level factors which have been demonstrated to differ considerably between public and Catholic schools. These include the number of math courses required for graduation in the academic track (MATHREQ), school climate variables describing such things as discipline (DISCLIM), the lack of academic emphasis in the school (AVLACKAC), the average number of academic math courses students take (AVMTHEMP), and the variability among students in math course enrollment (SDMTHEMP).

The second set of HLM models -- using math course enrollment as the first-stage outcome -- look very similar to those described in Model 1 thorugh 5 above, except for a different 'Base' variable. However, less extensive analyses analyses for that outcome are included in this paper. Specifically, although the first-stage model is consistently similar to Model 1, second-stage models proceed only though steps (a) to (d) shown above. The hierarchical linear modeling program represents a major methodological development in analyzing the effects of schools on their students. It is computationally complex but conceptually straightforward. I believe that the use of the hierarchical linear modeling approach to the questions posed in this paper is a useful addition to the tools available to educational researchers to look at how schools affect students.

RESULTS

An abbreviated form of the exact computer output for all analyses in this paper is presented in the Appendix. These printouts include both the Gamma(*) table, which lists the "regression" coefficients for second-stage analyses in each of the several models described above, and tables of estimated parameter variances for the intercepts and slopes, after taking the second-stage variables into account. Tables 1-A through 7-A describe the series of models using math achievement as the within-school dependent variable; Tables 1-B through 4-B examine math course enrollment as the first-stage dependent variable. All within-school models regress minority status, social class, and academic background on those two outcomes.

Hierarchical Models on Math Achievement. Other research has confirmed that the relationship between social class and math achievement is lower in Catholic than in public schools. However, unless slopes are flatter and intercepts are higher, a lower relationship between SES and achievement would indicate only that students in such schools were uniformly doing poorly. Similarly, if minority status were positively related to achievement, but mean achievement low, this would mean that students were doing poorly withough regard to race/ethnicity. Therefore, a search for "ideal variables" involves trying to identify variables which show a positive (and statistically significant) relationship to the intercept for achievement , a positive relationship with the minority/achievement slope, and a negative relationship with the SES/achievement slope. Table 1 documents effect sizes (given as gamma coefficients as explained above) on both school mean math achievement (the intercept) and on the three slopes (minority status on achievement, SES on achievement, and academic background on achievement) for the school sector variable under several different models. The metric for the gamma coefficients is unstandardized; that is, the magnitude of the effects in in points on a math achievement test.

Insert Table 1 about here

Since the 'sector' variable is coded '1' for Catholic schools and '0' for public schools, the gamma(*) coefficient for this variable represents the Catholic school effect. In the first column of Table 1, we can see that the mean achievement of Catholic schools is significantly higher (i.e. achievement intercept) and that the "sector effect" on two of the three slopes is also positive and significant. There is a negligible Catholic school effect on the academic background/achievement slope. These results indicate that in this model, Catholic schools have higher average achievement than public schools, as well as a positive sector effect on two of the relationships (i.e. slopes) in question. These results are adjusted for student difference in race/ethnicity, SES, and academic background between the two school sectors. We could conclude at this stage that although Catholic schools appear to produce high achievement, on average, and induce higher achievement in minority students, once social class is controlled, they also show a slightly higher SES/achievement slope.

We know, however, that students in Catholic schools are of higher social class, on average. Therefore, we should not evaluate the effect of school sector without having adjusted for those school social class differences. Having adjusted for social class <u>within schools</u> is not the same thing as adjusting for these average SES differences <u>between schools</u>. In fact, this is just what "social context" is all about. In one sense, the context effect can be typified as the <u>interaction</u> between student- and school-SES. Column 2 of Table 1 shows the effect of adjusting the school sector effect for the average social class differences between schools. The sector effect for average math achievement has been reduced in magnitude, but is still highly significant (that is, the "Catholic school achievement advantage" is still present. However, the sector effect on the SES slope has changed direction, although no longer significnant. That is, once schools are equalized for average SES, or context differences, we find that Catholic schools are still significantly higher in achievement than their public school counterparts, but the sector effect now shows just the set of characteristics described above as ideal: positive on achievement, positive (and close to significant) on the minority slope, and negative on the SES slope. Recall that this is after having adjusted, in first-stage regressions, for the differences in academic background between students.

We know that minority students are quite likely to be concentrated in high-minority enrollment schools, and that is particularly true in public schools (Coleman et al., 1982). Therefore, adjusting for this additional characteristic of schools could change the sector effect. However, introducing a further adjustment for this additional contextual characteristic of schools (compare the figures in Columns 2 and 3 of Table 1) appears to have almost no additional effect on the Catholic sector effect, probably due to the fact that the two contextual variables are highly correlated. This would indicate that even after controlling for the contextual variables of average SES and high-minority enrollment, which we know are considerably different across sectors, Catholic schools still appear to produce higher achievement, and to be moderately equalizing in terms of minority status, SES, and academic background.

The addition of certain other variables which relate to curriculum differences in schools to the models (Columns 4 and 5) changes results in an interesting way. Other research (Bryk, et al., 1984; Lee, 1985) has indicated that certain curricular differences between Catholic and public schools affect the social distribution of achievement in the two types of schools. Specifically, it appears that the more restricted curriculum offerings in Catholic high schools in fact leads students to take more academic courses, which in turn induces higher academic achievement. The results shown in Column 4, where the number of math courses offered in the school (MATHOFF) is introduced, confirms these earlier findings. We can see that once the breadth of the math curriculum is taken into account, the Catholic sector effect on achievement is diminished, but the more equalizing effect evidenced by a higher SES/achievement slope is increased. When an additional adjustment is made for the number of math course required for graduation (for academic track students only), in fact the Catholic sector effect on achievement and on the minority slope are greatly magnified, whereas the SES/achievement slope effect is eliminated. Although the math requirements variable is not directly related to the curriculum for all students in a school, we can see that the number of math offerings and the number of math requirements affect the Catholic sector effect very differently.

These finding support the contention of two recent books on the effect of curriculum breadth and variety on the equity of educational outcomes in American secondary schools (Cusick, 1983; Power, Farrar & Cohen, 1985). Both of these reports decry the expansion of the public high school curriculum over the last decade into largely non-academic areas, allowing students toomany choices withong providing adequate information about the sometimes damaging consequences of those choices, in terms of students' educational and professional futures.

"Explaining Away" the Catholic Sector Effect. The final HLM second-stage model displayed in Column 6 of Table 1 is perhaps the more interesting set of results presented thus far. This model is considerably more complex than the other five models displayed in this table, since different variables have been introduced for each second-stage analysis. The final model is the result of considerable experimentation with different sets of school factors. The exact variables in each "regression" are detailed in Table 7-A of the Appendix. However, we can see that this complex model has in fact "explained away" the Catholic sector effect on both the math achievement intercept and each of the slopes. As stated early in this paper, the aim of these HLM analyses was to identify particular characteristics of schools that explain why Catholic schools seem to (a) induce higher average achievement in their students, and (b) produce these academic outcomes in a more socially equtable manner.

A. The Intercept. Those school characteristics which appear to account for the average math achievement differences between Catholic and public schools include the contextual variables (average SES and high-minority enrollment), as well as three specific school climate variables. Please refer to Table 7-A of the Appendix for details. Most important (and highly and positively significant) is the average number of math courses students take in the school. We know that, on average, Catholic school students take many more math courses than their public school counterparts, and so this factor served as a strong explanatory variable in "explaining away" Catholic/public achievement differences. Another significant factor is the disciplinary climate of the school. Since this variable includes both an aggregate measure of disciplinary problems among students in their schools as well a principals' ratings of the disciplinary climate of their schools, its effect is negative. A third climate factor is composed of average student responses to a questionnaire item relating to the need for "more emphasis on basic academic subjects (math, science, English, etc.)" (NCES, 1980, p. 8-83). As the variable was coded so that less academic emphasis received a higher rating, the effect is negative. Taken as two sets (contextual factors, school climate factors), controlling for these factors effectively eliminates the previously observed strong Catholic school achievement advantage.

B. The Slopes. The set of school characteristics which explains away the previously observed Catholic school achievement advantage for minority students is smaller. Taking into account the concentration of minority students in high-minority schools and the disciplinary climate of the school effectively eliminates Catholic/public differences in the minority/achievement slope. A different set of school characteristics and policies explains the sector differences in the SES/achievement slope. The contextual variables of average school SES (which explains the fact that more affluent students are likely to be grouped in more affluent schools, on average) and the number of math courses offered by each school together account for the sector difference on the SES/achievement slope. Although the Catholic sector effect on the slope of academic background on achievement has never been large in the models presented thus far, that effect is totally eliminated by taking into account only two variables: the average academic background of students in each school (another contextual factor) and the variablity of math course enrollment in schools.

Thus, the HLM technique has allowed us to isolate a relatively small number of school characteristics -- particularly contextual and school climate factors -- which completely explain two phenomena which have dominated recent research which has used HS&B to compare student progress in Catholic and public schools. These phenomena, highly debated and often discussed in the recent literature on school effects, are (1) the fact that Catholic school students exhibit higher achievement levels than public school students, on average; and (2) the fact that Catholic schools appear to more equitibly distrubute such achievement across all social strata.

Hierarchical Models on Math Course Enrollment. Table 2 presents an HLM analysis roughly parallel to that presented above, except that within-school regressions have computed the effect of minority status, SES, and academic background on student enrollment in academic math courses. Since we know that there is a strong relationship between math course enrollment and achievement in mathematics, we would expect a similar pattern of results. A high intercept in first-stage results would indicate a school where the average of student course enrollment was high. A low slope on SES/course enrollment would typify a school where social class was not highly ralated to course choices. Other research (Lee, 1985) has shown that these relationships also vary across school sectors, with both minority status and social class less highly related to both course enrollment and to achievement in Catholic schools. Again, schools with high intercepts, positive minority slopes, and low SES slopes would be schools where students take many math courses and which are also equalizing in that course selection pattern. This high-intercept, low-slope pattern is the ideal, just as in the models which consider achievement. Again, the analysis involves a search for variables which fit this ideal. However, the models which examine math course enrollment as the first-stage outcome are simpler and less numerous than those which examined achievement.

Insert Table 2 about here

There are certain patterns which are similar to the achievement analyses. Again, the sector effect on the intercept is decreased when average SES is taken into account, but continues to be highly significant (compare Column 1 with Column 2 results on the math course intercept, which goes from 1.1 to .8). It should be noted that the metric of math course enrollment is in years of math, so that these Catholc sector effects are substantial. Also, the effect of school sector on the SES/course enrollment slope changes sign when school average social class is considered (compare Column 1 with Column 2 results in Table 2 on the SES slope). The sector effect goes from +.090 to -.121, with the latter coefficient close to statistical significance. On the other hand, the Catholic school minority slope advantage is significant in both instances, but in fact increases once average SES is taken into account. The additional second-stage contextual control for high-minority schools again makes little difference (comparing Columns 2 and 3), since average SES is already taken into account.

There is an important difference between the course enrollment and achievement models. In the case of achievement, the sector effect for mean achievement across schools becomes considerably smaller (less than two points on a test whose standard deviation is 7 points), once school average social class is taken into account. In the case of math course enrollment, the mean course enrollment differences between the sectors continues to be large and significant, even when adjusting for several school-level differences. A difference of .8 years of math for a variable whose standard deviation is 1.5 is considerable. Minority students in Catholic schools take over .3 years more of math than those in public school, even after the cross-sector differences in both social class and academic background are controlled for, as well as the contextual differences across schools and across sectors. This indicates that Catholic schools are both higher on average course enrollment and more socially equalizing on course enrollment, the "ideal" situation. In contrast with the results of the last analyses, the effect of Catholic sector on the slope of academic background on the first-stage dependent variable is significicant and negative, once the school context factors are introduced. In effect, controlling for academic background in first-stage regressions is an attempt to adjust for intake selection differences. Future research with HLM will attempt to isolate the set of school characteristics which explain away the even greater Catholic/public difference in math course taking. I suspect that restricted curriculum offerings would be important to explaining the persistent Catholic school effects seen in Table 2.

Cooperative Supression. Why does the effect of school sector on the slopes of both minority status and social class on either achievement or math course enrollment often increase or change sign once average social class is introduced into second-stage equations? This is an example of a phenomenon known as cooperative supression. Cooperative supression can be explained by the relative relationships between three variables such that the variables are "mutually enhancing" (Cohen and Cohen, 1975, p.91). In the present case, we observe the following correlational pattern. Average social class and the SES/achievement or SES/coursetaking slopes are positively related, as are sector and average social class. That is, Catholic schools have a higher mean SES. However, sector is negatively related to the slope. When two of the three relationships are positive and the third is negative, we find an increase in an effect when all three relationships are simultaneously evaluated. This suppression phenomenon indicates that the variables should be evaluated only as a set and not independently of one another. That is, the effect of school sector on the slope of either minority status or social class on either achievement or course enrollment should be evaluated only with average social class being simultaneously controlled. The fact that additional control for high-minority schools added little to the analysis is explained by the fact that these two contextual variables are strongly related to one another.

Variance Explained Between Schools. Due to the more accurate estimation of parameter variances with HLM procedures, we are able to determine the proportion of variance in estimated parameters (i.e. school mean achievement, mean course enrollment, and slopes) explained by the various models investigated in these analyses. This is accomplished by comparing parameter variances left to be explained by second-stage models to that unexplained in unconditional models (i.e. those with no second-stage variables). Table 3 presents the proportions of parameter variance explained by each set of second-stage variables making up the several models for mean school math achievement, and the between-school minority/achievement and SES/achievement slopes. As stated above, the effect of sector is best evaluated simultaneously with average school social class, because of supression effects.

Insert Table 3 about here

We can see that sector plus average social class together account for 52.7 percent of the parameter variance in mean achievement, 40.3 percent of the minority/achievement slope variance, and almost entirely explain the SES/achievement slope variance (an "R^2" of 89.9 percent). However, sector alone accounts for a much smaller amount of variance in both the intercept and the SES/achievement slope. Recall that the sector effect on the SES slope changed from positive to negative when average social class was introduced (Table 1 shows the effect decreases from +.70 to -.38), so it could be assumed that the change is entirely due to the contribution of school social class. However, the increase in the "R^2" for the minority/achievement slope was raised considerably after including high-minority schools into the model (compare steps 2(b) and 3(b) of Table 3). Looking down the list as the models become more complete, it is clear that additional variables contribute to the explanatory power of the models. However, these additional variables (math offerings and math requirements) add little more to the proportion of variance explained in school achievement means, the minority/achievement slope, or the SES/achievement slope than the proportion of variance explained by only sector and school context variables (Steps 2 and 3).

The pattern is slightly different for models which investigate math course enrollment in the first stage (see Table 4). In fact, sector alone explains a sizable amount of the variance in mean course enrollment (29.7 percent), and that proportion goes up moderately (to 53.4 percent) when average social class is taken into effect. Recall that, in math course enrollment models (Table 2), the sector effect does not decrease as much when average social class is controlled for as is the case with achievement. Notice that the sector effect on the SES/math course slope does not increase markedly when controlling for school social class (from 17.5 percent to 25.1 percent). The third model, which considers the additional contribution of high-minority schools adds little to the explanatory power of the model on all three parameters, including the minority slope.

Insert Table 4 about here

Therefore, we see that second-stage variables can explain a sizable proportion of the variance in these between-school slope and intercept parameters (well over 50 percent for the models on achievement, and over 90 percent for the SES/achievement slope). The models do a better job of explaining achievement that math course enrollment, where the latter models appear to have a stronger and more "resistant" sector effect. Previous work with slopes-as-outcomes generally has found only modest explanation for the slopes, because the overall variance in the slopes was not separated into its parameter and random components. Of course, only the actual parameter variance is explainable, and with HLM's ability to isolate and quantify that portion of the overall variance, the ability of the researcher to identify the explanatory power of these school-level factors is considerably augmented.

Slopes and Intercepts. A. SES on Math Achievement. The premise upon which this paper began was that the slope between social class and achievement was lower in Catholic than in public schools and the intercept (average achievement) was higher. In these analyses, we have investigated that slope and intercept extensively using hierarchical linear modeling. Figure 1 shows the HLM results from the analysis in which only school sector is entered as a school variable, with both the SES/math achievement slope and the mean math achievement intercept adjusted for individual student minority status and academic background. We can see that the mean achievement differences which favor Catholic schools are considerable (i.e. the lines are quite far apart), but that the slopes for Catholic and public schools are similar (See Note 7 for the souces of information and method for creating these graphs). However, where these same results are adjusted for the social context of the school (Figure 2), certain changes are noticeable. First, both slopes are steeper (original slopes were .74 and 1.44 respectively for public and Catholic schools; after adjusting for school social context, they climbed to 4.11 and 3.73). Second, unlike the pattern in Figure 1, where these lines were almost parallel but the slope in Catholic schools slightly steeper, here we see the Catholic slope slightly flatter. That is a confirmation of the fact that disadvantaged students benefit from Catholic school attendance. Were these lines continued to the right, they would eventually cross, indicating that for the very most affluent students, public schools are likely to be better. That finding is consistent ith the findings of Raudenbush and Bryk (1986) and with Greeley's (1982) conclusions on the HS&B base-year sample.

Insert Figures 1 and 2 about here

The power of the final model whose results were presented in Column 6 of Table 1 -- in which the Catholic sector effects on both mean achievement and the SES/achievement slope are explained away -- can be demonstrated graphically. In igure 3, we see that both the intercept (i.e. average achievement) difference between Catholic and public schools has virtually disappeared. Even more impressive is that the slope differences, as well as the magnitude of the slopes themselves, have also disappeared. This graph dramatically demonstrates that once the previously described sets of context and climate factors which vary between Catholic and public schools have been introduced into these models, the schools are "identical", in terms of achievement levels and the social distribution of that achievement.

Insert Figure 3 about here

B. Minority Status on Achievement. A similar set of graphs presents these same analytic steps for the relationship between minority status and math achievement. Figure 4 shows the analyses, with the only second-stage control being for school sector. Under these circumstances, the slopes of the lines are negative in both Catholic and public schools (indicating that minority students show lower average achievement than whites in both types of schools), but that the relative achievement differential for the two racial groups is greater in public schools (i.e. a slightly steeper negative slope for public schools). Also the "intercept" difference is less than for the corresponding SES/slope shown in Figure 1. From this graph, we could conclude that average achievement for all students is slightly less in public than Catholic schools, and this is especially true for minority students.

Insert Figures 4 and 5 about here

As stated earlier, it is inappropriate to evaluate the effects of school sector separately from the social context differences between the sectors. Figure 5 (which corresponds to Figure 2 for SES), shows the sector differences in the minority/achievement slope, once social context is taken into account. The nature of the graph has changed considerably. Most noticeable, the slopes of both lines have turned positive. This indicates that when the fact that minority students tend to be concentrated in high-minority (and lower-SES) schools is controlled, minority students achieve above whites. Of course, these results are also adjusted for student SES and academic background differences within each school. Note that the slope is even more steeply positive in Catholic than public scho , indicating that the adjusted "minority advantage" is somewhat stronger for the schools in the Catholic sector. However, the achievement differences between the two sectors, which favor Catholic schools, are somewhat stronger for this model (i.e. the lines are father apart than in Figure 4).

The graphical representation of the final model on the minority/achievement slope shown in Figure 6 (also from Table 1, Column 6) looks surprising similar to that for the SES/achievement slope shown in Figure 3. That is, the intercept differences between the sectors is gone, and so is the slope. When that particular set of school context and climate factors is introduced into the model, the schools in the two sector become synonymous in terms of average math achievement and the relationship of minority status to achievement. Note that the statistical controls for the slope are exactly the same for the two models shown in Figures 3 and 6, but that the particular school factors that explain away the Catholic sector effect on the minority/achievement slope (high-minority schools and disciplinary climate) are different from those which eliminate the Catholic school effect on the minority/achievement slope (average SES and the number of math courses offered). This might be interpreted to mean that in addition to school context (important for both slopes), what makes schools more equalizing for minorities is a positive disciplinary climate, but what induces equality for students from different social strata relates more to curricular differences. However, since minority status and SES are far from independent of one another, it is likely that both a positive school climate and a more restricted curriculum relate to social equality in all schools.

Insert Figure 6 about here

Thus, we see that the hierarchical approach allows a more refined look at both slopes and intercepts than has been attempted in previous research on the question of the achievement and equity differences in Catholic and public secondary schools. Of course, such analyses make an assumption of a linear relationship between SES or minority status with achievement, or between minority status and SES with math course enrollment. That is, HLM belongs within the set of methodological tools which may be used to explore the general linear model. However, we have been able to adjust these models for confounding variables both within schools (where academic background, minority status, and SES of students were controlled for) and between schools (where the effects of school social context and certain school climate factors were explored). Since these analyses, as well as many other research studies in recent years, have investigated the differential effects of Catholic and public schools, the ability to adjust for "selection differences" at two analytic levels reduces claims of selection bias even further. In fact, in one analysis, the between-sector differences were completely explained.

DISCUSSION

Hierarchical linear modeling has allowed the identification of specific school characteristics and policies which help to explain several relationships which are of primary concern in this paper: the relationship between social class and minority status with math achievement, the relationship between social class and minority status with math course enrollment, and school means for achievement and for course enrollment. In fact, the major explanatory variables which have emerged from these analyses as predictors of all of the relationships of interest fall into a small number of categories. First, we have shown that there are considerable differences between the schools in the Catholic and public sectors on these outcomes, differences which favor Catholic schools. Second, we have seen that three sets of factors can effectively explain away those cross-sector differences: (1) variation in the social context of schools in the two sectors; (2) variation in the academic and disciplinary climate among schools in the sectors; and (3) variation in curricular offerings and requirements. Results from previous research that have concluded that Catholic schools induce consistently higher mean achievement and mean course enrollment in their students must now be somewhat refined. The Catholic schools' advantage in mean school math achievement and the more equitable distribution of that achievement appears to be explainable by the school-related factors described above. The fact that these Catholic sector advantages are explainable by a reasonably modest set of school characteristics and policies is noteworthy.

In fact, the real value of HLM in this context is exactly the ability it affords researchers to answer this important educational question: What are the specific features of Catholic schools that make them more egalitarian? From these analyses, a set of tentative conclusions may be drawn. Specifically:

- School social context is an important factor in explaining achievement and educational equity in both sectors. Although we know that affluent students as well as poor (or minority) students tend to be unequally grouped in schools and are more likely to be grouped with students like themselves, we know that this is less the case in Catholic than in public high schools. Clearly, schools with high average SES ratings, and schools where there is a low concentration of minority students, show higher average achievement. However, if we are interested in high achievement being broadly demonstrated by students from a variety of social backgrounds, such concentrations of students in schools typified by extremes of social composition should be ameliorated, since they decrease equity within schools. This would indicate that a broader distribution of social class and minority mix in schools should contribute to a more socially equitable distribution of educational outcomes.

- School climate factors act as important determinants of both high achievement and equity. In particular (and not surprisingly), a positive disciplinary climate, where fewer students are involved in incidents of a disciplinary nature, induces high average achievement for all students, and a more equitable distribution of achievement across different racial/ethnic groups.

- A positive academic climate is likewise a strong determinant of high average achievement. That sort of climate within a school is characterized by a high average math course enrollment among students, and by students who believe their schools are not underemphasizing academic subjects like math, science, or English.

- Variations in school curricular offerings have some effect on the factors considered in this paper. Not only are schools where students take more math classes higher achieving schools, on average, but schools which offer a more restricted set of math courses seem to promote a more equitable distribution of achievement across students from different SES levels. This might indicate that less choice was related to both higher achievement and more equitably distributed outcomes. Moreover, there is some evidence that schools which show more variability in the number of math courses students take promote less equality in the relationship between students' academic background when they come to high school and their subsequent achievement.

These analyses have presented some hopeful empirical evidence about the ability to assess the effects of schools on students in several respects. First, it appears that this relatively new and experimental technique is able to tease out interesting school-student relationships that have been posed by both researchers and school people for several years, whereas the investigation of such questions has produced disappointing results in the past. Although the HLM method requires extensive multi-level data on students linked to information about their schools, increasingly, large national studies are gathering such data. Although I have left the statistical discussion necessary to justify the use of this technique to other authors (Mason et al., 1984; Raudenbush and Bryk, 1986), it is hoped that the explicit description of the use of this method within the context of a specific and appropriate school/student question has been useful to introduce users to this potentially valuable new technique.

There are certainly difficulties with the use of any new technique that requires some acceptance on the part of researchers unfamiliar with it. However, I am sure such difficulties befell early users of factor analysis, discriminant analysis, and even OLS regression. Now these procedures are employed routinely in social science research. The use of HLM requires statistical assumptions similar to those made by OLS. Additional distributional assumptions are necessary for the EM computations of standard errors, as well as the hypothesis testing involved. However, the difficulties of more stringent distributional assumptions are overcome by the advantage of HLM over OLS on a single dimension. That is, OLS assumes that within-school relationships are identical across schools. As such, least squares regression assumes that the relationship between social class and achievement is the same in every school. However, in this paper we have seen that these relationships vary considerably across schools, and we have seen in parameter variance estimates that after adjusting that relationship for a moderate set of school-level variables, almost all of that variation could be explained. In fact, many analyses in the paper have used the variation in that relationship as a dependent variable.

Second, and perhaps most interesting, is that the analyses presented in this paper, using the hierarchical linear modeling methodology, have been able to isolate certain school characteristics that seem to make a real difference in both student achievement and the relationship between that achievement and social characteristics of students. On the basis of the results presented herein, we are presented with a list of important school factors that seem to make a serious difference. However, the really difficult questions involve the implementation of findings described here. All of these questions seem to begin with "how." For example, "How may educators begin to implement a less stratified distribution of students into schools?" Or, "How is is possible to encourage a positive disciplinary climate, or a climate where students really care about academic concerns in schools?" Perhaps the hints about curriculum presented in this study are the easiest place to begin.

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TECHNICAL NOTES

1. The only circumstances under which aggregated and unaggregated parameter estimates are likely to be similar, according to Burstein (1978), are when one of the following conditions holds:

   (a) The grouping variable has no effect on the outcome, net of the covariate;
   (b) The grouping variable is independent of the covariate; or
   (c) The variance of the covariate at the individual and aggregated levels are identical.

   For investigating educational data of the sort treated herein, where the outcome is achievement, the grouping variable schools, and the covariate SES, it is hard to imagine that schools have no effects on their students' achievement <u>except</u> through their SES (condition a), that school grouping is not at all related to SES (condition b), or that the variance of SES at the individual and school-aggregate level is identical (condition c). It is generally the case that the variance of the aggregated variable is much lower than the same variable in disaggregated form. Therefore, these ideal conditions seldom, if ever, exist when grouping is not entirely at random.

2. Mason et al. (1984) give substantial detail on the statistical conceptualization of both the macro and micro models, and the restricted maximum likelihood estimation procedure. Please refer to their chapter for details. Essentially the same details are provided in Raudenbush and Bryk (1986). I argue for the use of these procedures in the sort of research described in this paper, but leave these researchers to spell out both the details of the procedure and the statistical arguments for its appropriateness.

3. The academic background variable used in these analyses is constructed of the following variables: (1) whether student had college expectations in the 8th grade; and (2) whether student had been placed in remedial math or English at high school entry. Clearly, this variable does not completely tap students' academic background before high school, but the two components are highly correlated with each other, and highly correlated with achievement. Intake educatinal aspirations have been shown to be an important selection criterion for Catholic and public school choice.

4. An almost identical HLM model has been previously explored investigating the SES/achievement relationship without taking minority status into account. Since these two variables are highly correlated (negatively), the results for SES without minority status were considerably different. Including both of these demographic characteristics of students in first-stage models was decided to represent the best conceptualization. However, the results are that SES/ achievement slope results in these analyses appear considerably weaker. Each effect is <u>net</u> of the other.

5. The percent of minority students enrolled in the school was first investigated employed as a continuous variable. However, it appears that minority enrollment in the school has little impact on average academic performance of students at low proportions. When the minority enrollment reaches about 40 percent, mean school achievement appears to deteriorate as

a result of minority enrollment, on average. For that reason, a dummy variable was constructed, where schools of less than 40 percent minority enrollment were coded '0' and those with 40 percent or more minority enrollment were coded '1'. Although it could be considered that schools coded '1' might be called "segregated schools", the same would certainly be true for those coded '0' which enrolled no minority students at all.

6. Figures 1 through 10 have been constructed from data presented in Appendix. For example, the intercepts and slopes for Figure 1 come from Table 2-A results. Intercept figures are 9.596657 (the BASE) for public schools, (9.596657 + 3.632763--BASE + sector effect on BASE) for Catholic schools. The intercept figures are those where student SES = 0. Slopes are .740732 for public schools, (.740732 + .700068) for Catholic schools. Figures 2 and 3 results come from Tables 4-A and 7-A, and are constructed in the same manner. Results presented in Figures 4 through 6 come from Tables 2-A, 4-A and 7-A, respectively. Tables 7 through 10 use information from Tables 2-B and 4-B in the Appendix.

   Graphs of the SES/achievement slope are created by computing the appropriate intercept figures at SES values of -1, 0, and +1, given the slopes. These SES figures are equivalent to lower-middle, middle, and upper-middle class students. Recall that the original SES variable has been standardized on the Catholic sample, so the mean of 0 is "middle class" for students in Catholic schools. Of course, the presentation of these results assumes a linear relationship between SES and both math achievement and math course enrollment. This linearity is assumed throughout all analyses, in fact. Graphs of the minority/achievement slope are compute for values of '0' (white) and '1' (minority), in the manner described for SES.

3. Of the three achievement outcomes available for both 1980 and 1982 seniors in the HS&B study, mathematics was selected for several reasons. First, the math tests have been shown to be the most reliable of the HS&B base-year tests (Heyns & Hilton, 1982). Second, math is the test where particular courses in school are directly related to achievement (not so true for high school students in vocabulary or reading, the other two HS&B tests). Third, it has been shown that progress in mathematics is less related to characteristics of the home, and more related to school-based factors.

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Table 1

The Change in the Effect of School Sector on School Mean Math Achievement, Minority Group/Achievement Slope, SES/Achievement Slope, and Academic Background/Achievement Slope When Selected Factors are Controlled For

Effect Estimates of Sector From Second-Stage Analyses[1]

Sector Effect on:[4,5]	(2-A)[2] SECTOR	(3-A) SECTOR, AVSES	(4-A) SECTOR, AVSES, HIMTYSCL	(5-A) SECTOR, AVSES, HIMTYSCL, MATHOFF	(6-A) SECTOR, AVSES, HIMTYSCL, MATHOFF, MATHREQ	(7-A)[3] SECTOR, AVSES, HIMTYSCL, AVMTHEMP, AVLACKAC, DISCLIM, MATHOFF, AVACDBGD, SDMTHEMP
Achievement Intercept:	3.63***	1.98**	1.98***	1.17*	2.11***	-.17
Minority/Ach. Slope	1.85**	1.25	1.21	1.28	2.38***	.27
SES/Ach. Slope:	.70*	-.38	-.39	-.86	-.09	-.18
Academic Bkrd/ Ach. Slope:	.36	-.12	-.13	.00	-.17	.00

1
All analyses have been weighted at the second stage, using the school weight supplied from the HS&B study. First-stage (within-school) regressions are unweighted, since sampling within schools was close to random. Weighting applies to all analyses in this paper.

2
These numbers refer to the computer output from HLM runs presented in the Appendix.

3
In this analysis, different school-level factors are entered into the analyses for each first-stage outcome. Only SECTOR is included in all analyses. For details of which factors were used to predict each factor (average achievement or each of the 3 slopes), see Table 7-A in the Appendix.

4
Effects are presented as Gamma(*) coefficients from HLM analyses. These are roughly equivalent to unstandardized regression coefficients. The means for these "variables" (which include adjustment for first-stage variables) evaluated before any second-stage regressions are performed are: IRTMATH: 11.30; Minorty/ACH: -1.45; SES/ACH: 1.09; ACDBKGD/ACH: 2.51.
5
Nominal significance levels are taken from the Z-statistics of Tables 1-A through 7-A of the Appendix (* = $p < .05$; ** = $p < .01$; *** = $p < .001$).

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Table 2

The Change in the Effect of School Sector on School Mean Math Coursetaking, Minority Group/Math Course Slope, SES/Math Course Slope, and Academic Background/ Math Course Slope When Selected Factors are Controlled For

Effect Estimates of Sector From Second-Stage Analyses[1]

Sector Effect on:[2,3]	(2-B) SECTOR	(3-B) SECTOR, AVSES	(4-B) SECTOR, AVSES, HIMTYSCL
Math Course Intercept:	1.106***	.818***	.819***
Minority/Math Course Slope:	.283*	.337*	.335*
SES/Math Course Slope:	.090	-.121	-.123
Academic Bkrd/ Course Slope:	-.064	-.123*	-.122*

----

1 These figures refer to full computer output from HLM runs presented in the Appendix.

2 Effects are presented as Gamma(*) coefficients from HLM analyses. These are roughly equivalent to unstandardized regression coefficients. The means for these variables before any second-stage variables are entered are: MATHEMPH: 2.125; Minority/MTHEMPH: .206; SES/MTHEMPH: .304; ACDBKGD/MTHEMPH: .527.

3 Nominal significance levels are taken from the Z-statistics of Tables 2-B through 4-B of the Appendix (* = p < .05; ** = p < .01; *** = p < .001).

Table 3

Percent of Variance Explained in Average Math Achievement, the Minority/Achievement Slope, and the SES/Achievement Slope by the Addition of Various Second-Stage Variables.

Additional Variance Explained in (a) Average Math Achievement
(b) Minority Group/Achievement Slope
(c) SES/Achievement Slope by:

1. SECTOR

(a)	16.2%[1]
(b)	38.5%
(c)	8.0%

2. SECTOR + AVSES

(a)	52.7%
(b)	40.3%
(c)	89.9%

3. SECTOR + AVSES + HIMTYSCL

(a)	60.3%
(b)	62.7%
(c)	90.6%

4. SECTOR + AVSES + HIMTYSCL + MATHOFF

(a)	60.0%
(b)	59.8%
(c)	93.8%

5. SECTOR + AVSES + HIMTYSCL + MATHOFF + MATHREQ

(a)	60.2%
(b)	59.8%
(c)	96.2%

----

[1] The method used to calculate these increments in explained parameter variance involves the explained parameter variances presented at the bottom of Tables 1-A through 6-A in the Appendix. Comparing explained parameter variance in Math Achievement (BASE) on the unconditional model (1-A) with that in the model where only Sector is added (2-A), the computation is as follows:

$$(10.41524 - 8.73314) / 10.41524 = .1615 = 16.2\%$$

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Table 4

Percent of Variance Explained in Average Math Course Enrollment, the Minority/Math Course Slope, and the SES/Math Course Slope by the Addition of Various Second-Stage Variables.

Additional Variance Explained in (a) Average Math Course Enrollment
(b) Minority Group/Math Course
(c) SES/Math Course Slope by:

1. SECTOR

	[1]
(a)	29.7%
(b)	17.5%
(c)	40.6%

2. SECTOR + AVSES

(a)	53.4%
(b)	25.1%
(c)	47.4%

3. SECTOR + AVSES + HIMTYSCL

(a)	57.8%
(b)	29.1%
(c)	54.1%

---

[1] The method used to calculate these increments in explained parameter variance involves the explained parameter variances presented at the bottom of Tables 1-B through 4-B in the Appendix. Comparing explained parameter variance in Math Course Enrollment (BASE) on the unconditional model (1-B) with that in the model where only Sector is added (2-B), the computation is as follows:

(.57852 - .40664) / .57872 = .2973, or 29.7%

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FIGURE 1
HLM Results of Slope and Intercept for SES on Math Achievement:
No Control for Any School-Level Factors

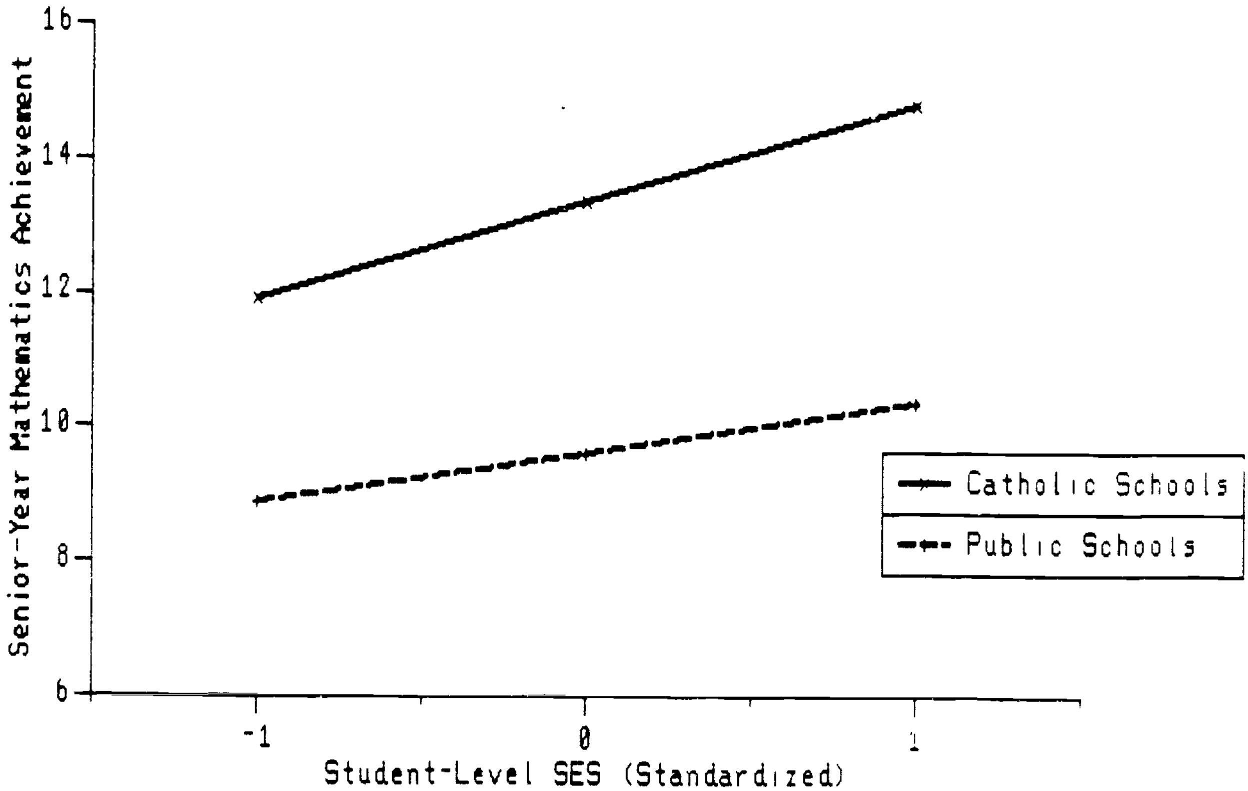


FIGURE 2
HLM Results of Slope and Intercept for SES on Math Achievement: Controls for Average SES and High-Minority School

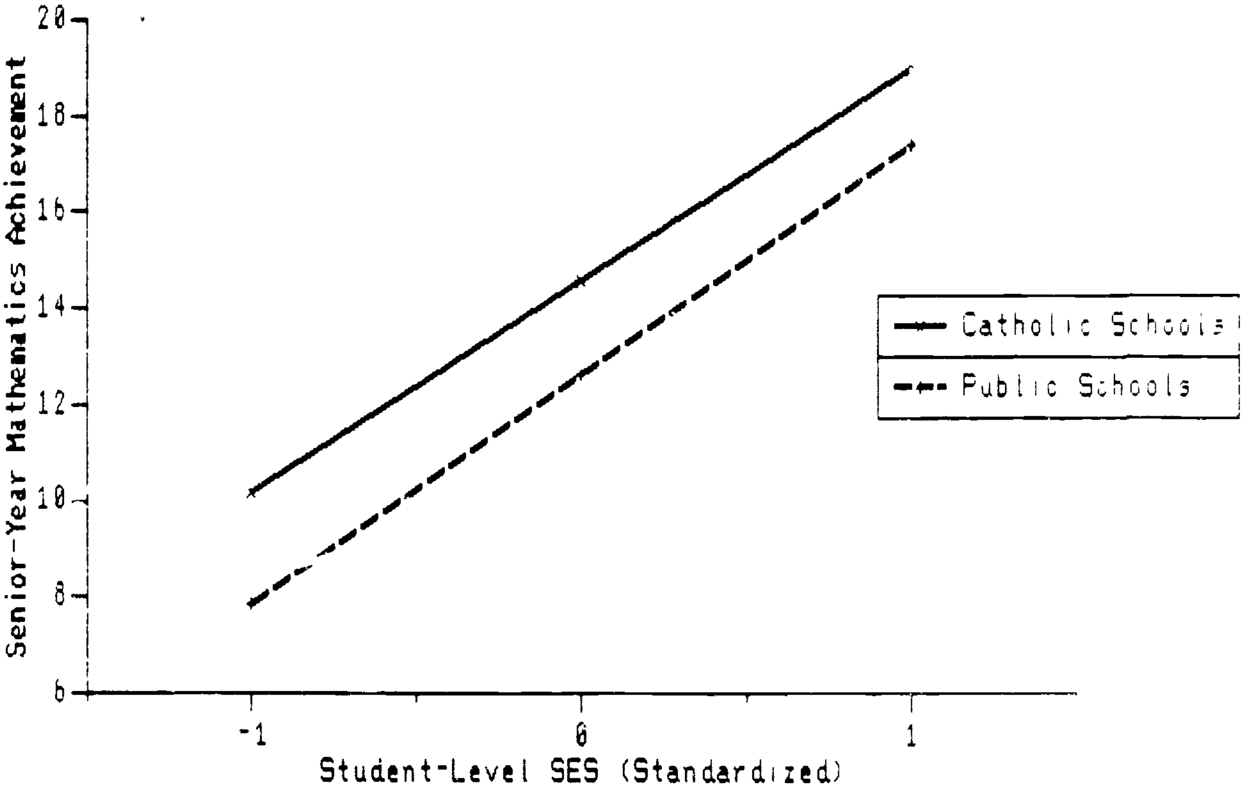


FIGURE 3
HLM Results of Slope and Intercept for SES on Math Achievement:
Controls for Full Model to Explain Away Sector Effect

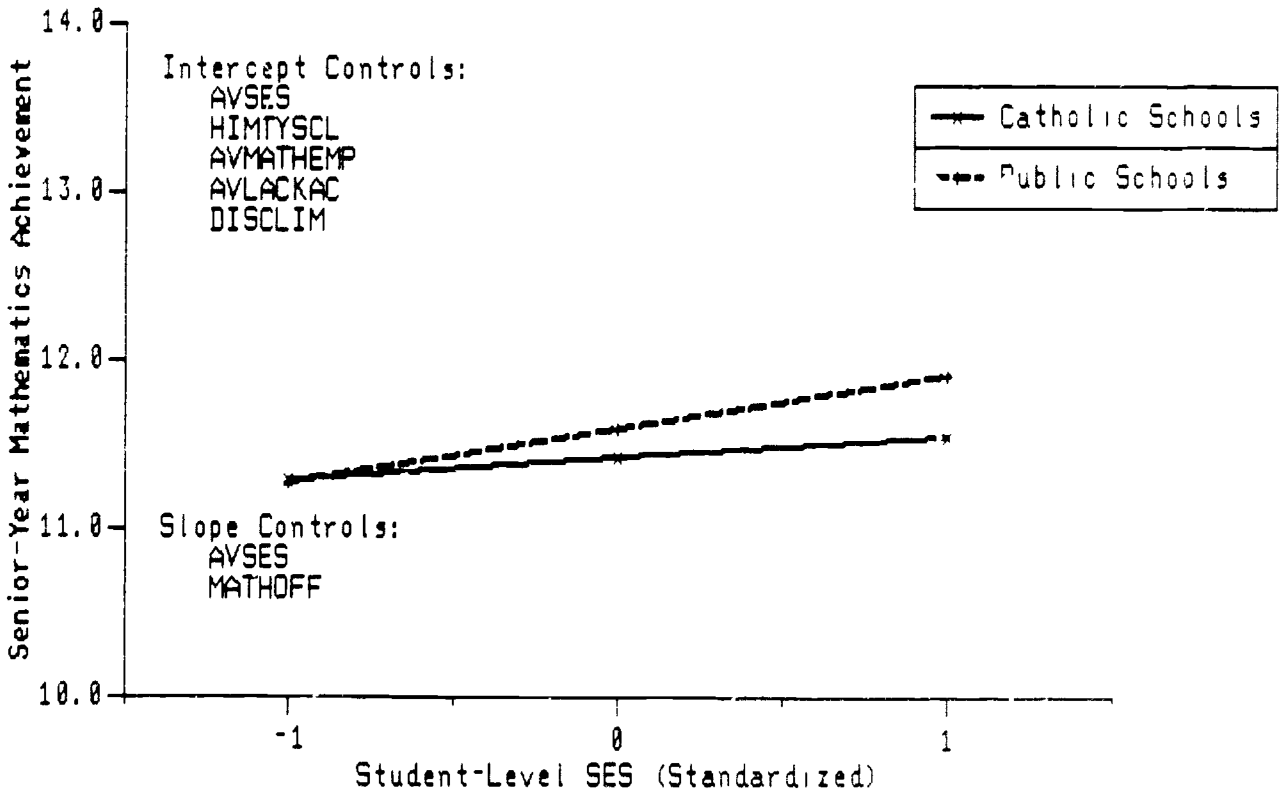


FIGURE 4
HLM Results of Slope and Intercept for Minority Status on Math Achievement:
No Controls for School-Level Factors

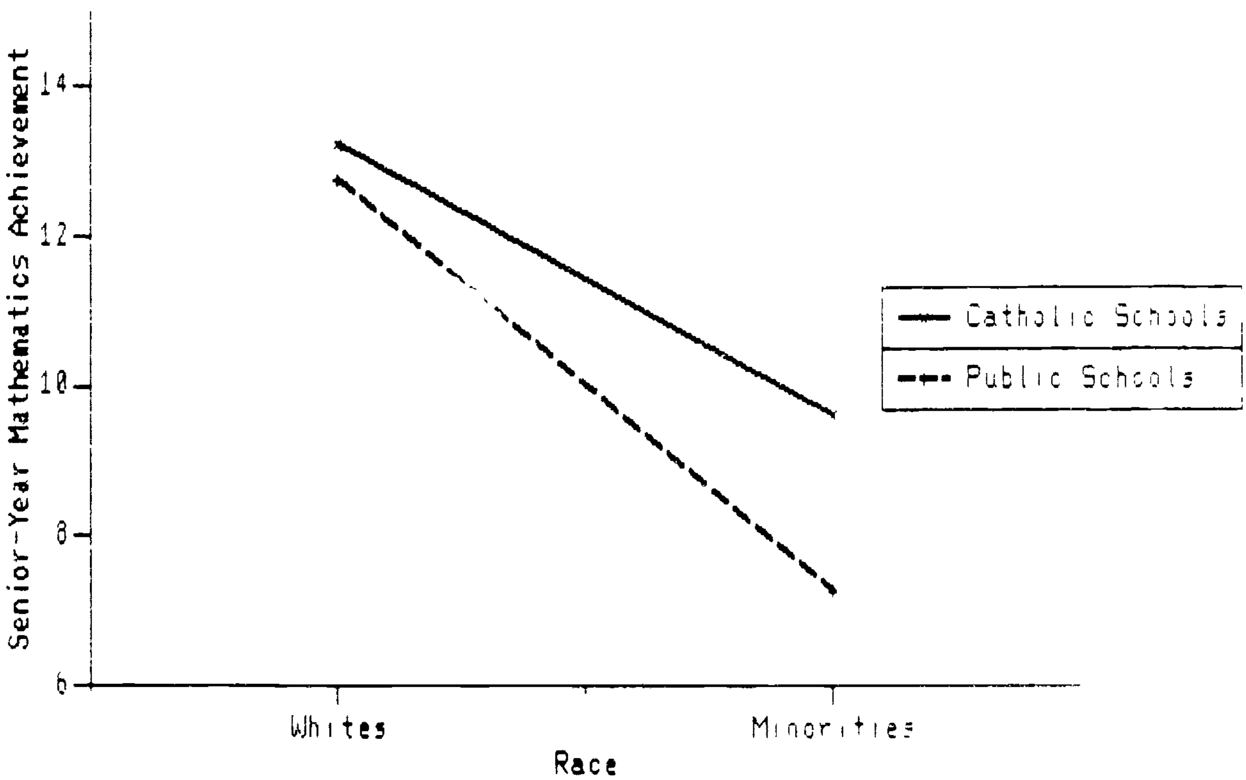


FIGURE 5
HLM Results of Slope and Intercept for Minority Status on Math Achievement: Controls for Average SES and Hi-Minority School

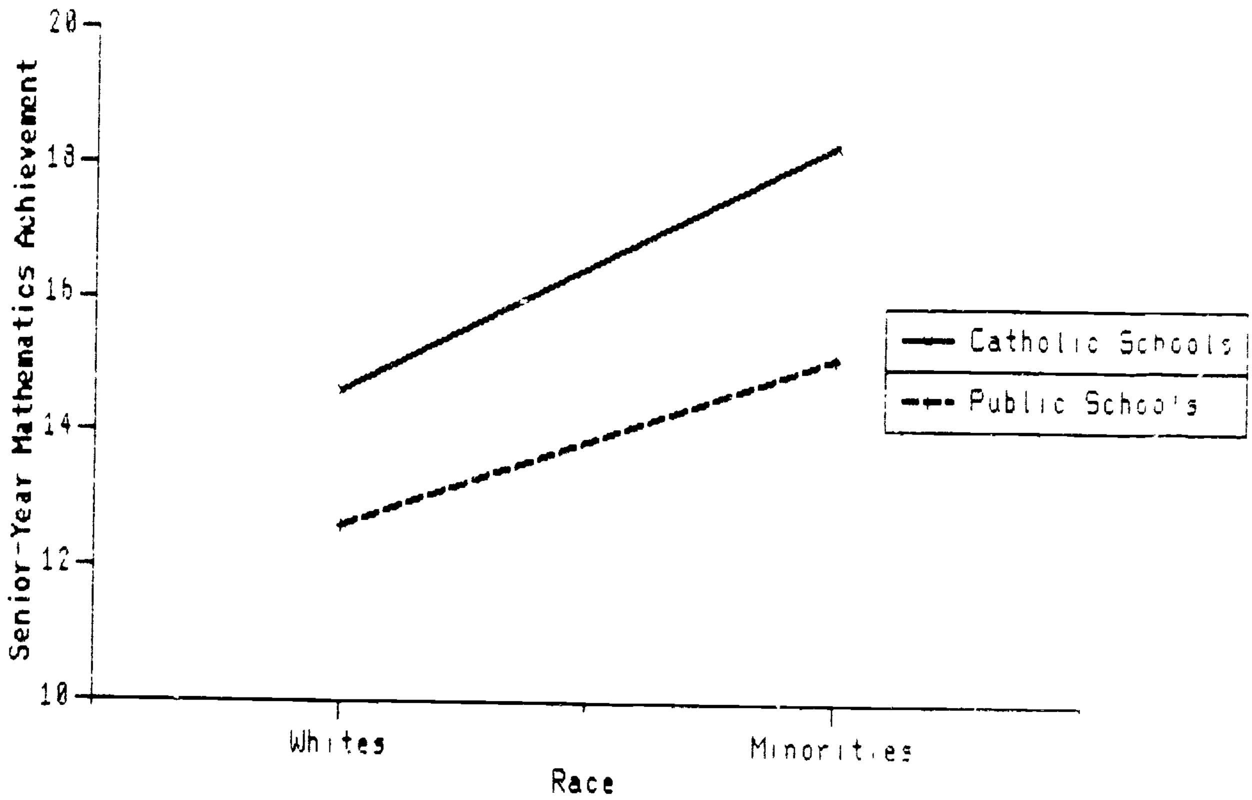
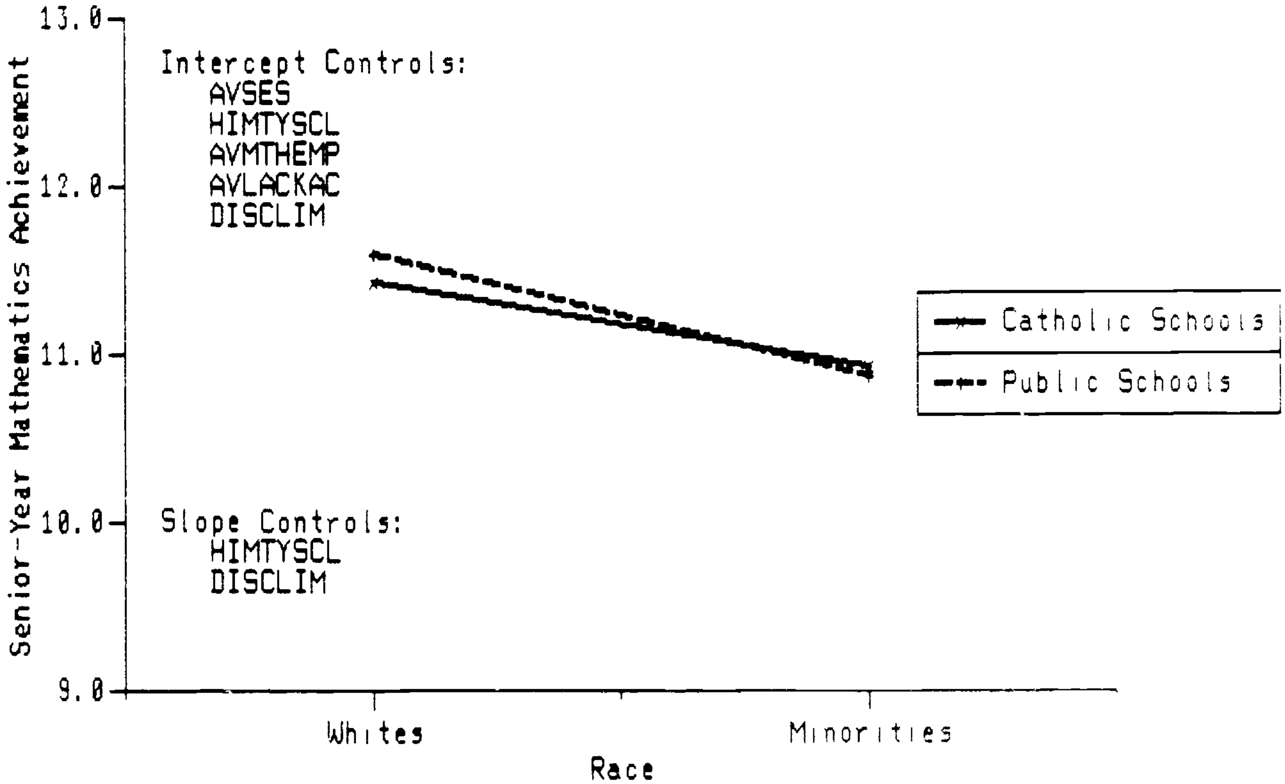


FIGURE 6
HLM Results of Slope and Intercept for Minority on Math Achievement:
Controls for Full Model to Explain Away Sector Effect



APPENDIX

COMPUTER OUTPUT FROM HIERARCHICAL LINEAR MODELING PROGRAM

Table 1-m: HLM Model of Minority Status, SES, and Academic Background on Math Achievement: Unconditional Second Stage

Model: Stage 1: IRTMATH = MNRTY80 + SES + ACDBKRD
Stage 2: Unconditional (0)

THE GAMMA(*)-STANDARD ERROR-Z STATISTIC TABLE:

	GAMMA(*)	STANDARD ERROR	Z STATISTIC	p-VALUE
For BASE				
BASE	11.304647	.269406	41.961	.000
For MNRTY80				
BASE	-1.448585	.350780	-4.130	.000
For SES				
BASE	1.089177	.149445	7.298	.000
For ACDBKGD				
BASE	2.507619	.110447	22.704	.000

THE PRECEEDING GAMMA(*) TABLE REFLECTS THE SPECIFIED WEIGHTING
THIS ANALYSIS WAS WEIGHTED USING TRIMWT

THE CHI SQUARE TABLE:

PARAMETER	ESTIMATED PARAMETER VARIANCE	DEGREES OF FREEDOM	CHI SQUARE	P-VALUE
BASE	10.41524	116	1091.7	.000
MNRTY80 slope	6.20264	116	[illegible]	.000
SES slope	1.22333	116	143.95	.000
ACDBKGD slope	.77102	116	[illegible]	[illegible]

Table 2-H: HLM Model of Minority Status, SES, [illegible] Achievement: School Sector at Second Stage.

Model. Stage 1: IRTMATH = MNRTY80 + SES + ACDBKGD
Stage 2: SECTOR

THE GAMMA(*)-STANDARD ERROR-Z STATISTIC TABLE.

	GAMMA(*)	STANDARD ERROR	Z STATISTIC	P-VALUE
For BASE				
BASE	9.586657	.344824	[illegible]	[illegible]
SECTOR	3.632763	.499119	[illegible]	[illegible]
For MNRTY80				
BASE	-2.338066	.426337	-5.484	[illegible]
SECTOR	1.848733	.623002	[illegible]	[illegible]
For SES				
BASE	.740732	.202132	[illegible]	[illegible]
SECTOR	.700068	.287912	[illegible]	[illegible]
For ACDBKGD				
BASE	2.335080	.156844	[illegible]	[illegible]
SECTOR	.361075	.225902	[illegible]	[illegible]

THE PRECEEDING GAMMA(*) TABLE REFLECTS THE SPECIFIED WEIGHTING
THIS ANALYSIS WAS WEIGHTED USING TRIMWT

THE CHI SQUARE TABLE:

PARAMETER	ESTIMATED PARAMETER VARIANCE	DEGREES OF FREEDOM	CHI SQUARE	P-VALUE
BASE	9.77314	115	[illegible]	[illegible]
MNRTY80 slope	3.31799	115	[illegible]	[illegible]
SES slope	1.12541	115	[illegible]	[illegible]
ACDBKGD slope	.82321	115	[illegible]	[illegible]

Table 3-[illegible]: HLM Model of Minority Status, SES, and Academic Background on Math Achievement: School Sector and Average Social Class at Second Stage.

Model: Stage 1: IRTMATH = MNRTY80 + SES + ACDBKGD
Stage 2: SECTOR + AVSES

THE GAMMA(*)-STANDARD ERROR-Z STATISTIC TABLE.

	GAMMA(*)	STANDARD ERROR	Z STATISTIC	P-VALUE
For BASE				
BASE	11.083446	.340453	32.555	.000
AVSES	4.030251	.582823	6.915	.000
SECTOR	1.975706	.456654	4.32[illegible]	.000
For MNRTY80				
BASE	-1.[illegible]34627	.580288	-[illegible]	.00[illegible]
AVSES	.830056	.854[illegible]	.9[illegible]	[illegible]
SECTOR	1.250473	.735004	1.70[illegible]	.08[illegible]
For SES				
BASE	1.678687	.227445	7.[illegible]	.000
AVSES	2.433536	.376055	6.47[illegible]	[illegible]
SECTOR	-.377324	.296505	-1.2[illegible]	[illegible]
For ACDBKGD				
BASE	2.748860	.189367	14.5[illegible]	.000
AVSES	1.105473	.315758	3.5[illegible]	[illegible]
SECTOR	-.123018	.247327	-.49[illegible]	[illegible]

THE PRECEEDING GAMMA(*) TABLE REFLECTS THE SPECIFIED WEIGHTING
THIS ANALYSIS WAS WEIGHTED USING TRIMWT

THE CHI SQUARE TABLE:

PARAMETER	ESTIMATED PARAMETER VARIANCE	DEGREES OF FREEDOM	CHI SQUARE	P-VALUE
BASE	4.93015	114	[illegible]	[illegible]
MNRTY80 slope	3.70073	114	[illegible]	[illegible]
SES slope	.12384	[illegible]	[illegible]	[illegible]
ACDBKGD slope	.60580	[illegible]	[illegible]	[illegible]

Table 4-A: HLM Model of Minority Status, SES, and Academic Background [illegible] Math Achievement: School Sector, Average Socio. Class, and [illegible] Minority Enrollment at Second Stage.

Model: Stage 1: IRTMATH = MNRTY80 + SES + ACDBKGD
Stage 2: SECTOR + AVSES + HIMTYSCL

THE GAMMA (*)-STANDARD ERROR-Z STATISTIC TABLE:

	GAMMA(*)	STANDARD ERROR	Z STATISTIC	P-VALUE
For BASE				
BASE	11.172559	.320333	34.87[illegible]	.000
AVSES	3.694848	.561309	6.58[illegible]	.000
SECTOR	1.981430	.427331	4.5[illegible]	.000
HIMTYSCL	-2.246803	.753679	-2.98[illegible]	.00[illegible]
For MNRTY80				
BASE	-1.954979	.565350	-3.458	.00[illegible]
AVSES	1.546739	.562105	[illegible]	.00[illegible]
SECTOR	1.206306	.704309	1.7[illegible]	.08[illegible]
HIMTYSCL	2.893047	.573671	5.0[illegible]	.00[illegible]
For SES				
BASE	1.660129	.231672	7.16[illegible]	.000
AVSES	2.517660	.397578	6.3[illegible]	.00[illegible]
SECTOR	-.391809	.301571	-1.29[illegible]	.[illegible]
HIMTYSCL	.602766	.452530	[illegible]	[illegible]
For ACDBKGD				
BASE	2.784597	.183675	14.8[illegible]	[illegible]
AVSES	.994152	.307164	3.2[illegible]	[illegible]
SECTOR	-.129235	.246534	-.52[illegible]	[illegible]
HIMTYSCL	-.640127	.337593	[illegible]	[illegible]

THE PRECEEDING GAMMA(*) TABLE REFLECTS THE SPECIFIED [illegible]
THIS ANALYSIS WAS WEIGHTED USING TRIMWT

THE CHI SQUARE TABLE:

PARAMETER	ESTIMATED PARAMETER VARIANCE	DEGREES OF FREEDOM	CHI SQUARE	P-VALUE
BASE	4.13448	[illegible]	[illegible]	[illegible]
MNRTY80 slope	2.01134	[illegible]	[illegible]	[illegible]
SES slope	.11452	[illegible]	[illegible]	[illegible]
ACDBKGD slope	.55010	[illegible]	[illegible]	

Table 5-A: HLM Model of Minority Status, SES, and Academic Background on Math Achievement: School Sector, Average Social Class, High Minority Enrollment, and Number of Math Courses Offered at Second Stage.

Model: Stage 1: IRTMATH = MNRTY80 + SES + ACDBKRD
Stage 2: SECTOR + AVSES + HIMTYSCL + MATHOFF

THE GAMMA(*)-STANDARD ERROR-Z STATISTIC TABLE:

	GAMMA(*)	STANDARD ERROR	Z STATISTIC	P-VALUE
For BASE				
BASE	11.083590	.603040	18.380	.000
AVSES	3.651236	.595576	6.131	.000
SECTOR	2.003528	.437198	4.583	.000
HIMTYSCL	-2.251467	.762897	-2.951	.004
MATHOFF	.006201	.039398	.157	[illegible]
For MNRTY80				
BASE	-2.924834	1.106434	-2.643	.009
AVSES	1.188383	.946387	1.255	.210
SECTOR	1.417426	.742975	1.908	.056
HIMTYSCL	2.698215	.897521	3.006	.003
MATHOFF	.072810	.068845	1.058	[illegible]
For SES				
BASE	.834090	.427674	1.950	[illegible]
AVSES	2.159613	.413940	[illegible]	[illegible]
SECTOR	-.223204	.304722	-.772	[illegible]
HIMTYSCL	.430708	.451515	.954	[illegible]
MATHOFF	.062345	.027396	2.279	[illegible]
For ACDBKGD				
BASE	2.186426	.349867	[illegible]	[illegible]
AVSES	.743061	.347362	[illegible]	[illegible]
SECTOR	-.010571	.252089	[illegible]	[illegible]
HIMTYSCL	-.772681	.403363	[illegible]	[illegible]
MATHOFF	.045838	.022741	[illegible]	[illegible]

THE PRECEEDING GAMMA(*) TABLE REFLECTS THE SPECIFIED WEIGHT[illegible]
THIS ANALYSIS WAS WEIGHTED USING TRIMWT

THE CHI SQUARE TABLE:

PARAMETER	ESTIMATED PARAMETER VARIANCE	DEGREES OF FREEDOM	CHI SQUARE	[illegible]
BASE	4.14243	[illegible]	[illegible]	[illegible]
MNRTY80 slope	2.49293	[illegible]	[illegible]	[illegible]
SES slope	.04675	[illegible]	[illegible]	[illegible]
ACDBKGD slope	.55455	[illegible]	[illegible]	[illegible]

Table 6-A: HLM Model of Minority Status, SES, and Academic Background and Math Achievement: School Sector, Average Social Class, High Minority Enrollment, Number of Math Courses Offered, and Number of Math Courses Required at Second Stage.

Model: Stage 1: IRTMATH = MNRTY80 + SES + ACDBKGD
Stage 2: SECTOR + AVSES + HIMTYSCL + MATHOFF + MATHREQ

THE GAMMA (*)-STANDARD ERROR-Z STATISTIC TABLE:

	GAMMA(*)	STANDARD ERROR	Z STATISTIC	P-VALUE
For BASE				
BASE	11.516589	.694419	16.535	[illegible]
AVSES	3.710021	.598026	6.19[illegible]	[illegible]
SECTOR	2.111473	.445851	4.735	[illegible]
HIMTYSCL	-2.180326	.767847	-2.840	[illegible]
MATHREQ	-.271506	.215242	-1.261	[illegible]
MATHOFF	.006872	.039479	[illegible]	[illegible]
For MNRTY80				
BASE	-3.316767	1.285988	-2.573	[illegible]
AVSES	1.174209	.953390	[illegible]	[illegible]
SECTOR	1.282640	.790933	1.622	[illegible]
HIMTYSCL	2.685951	.904146	2.971	[illegible]
MATHREQ	.236662	.421330	.562	[illegible]
MATHOFF	.074504	.068677	1.08[illegible]	[illegible]
For SES				
BASE	1.318520	.501778	[illegible]	[illegible]
AVSES	2.256264	.425477	[illegible]	[illegible]
SECTOR	-.098767	.312689	-.316	[illegible]
HIMTYSCL	.584944	.460913	[illegible]	[illegible]
MATHREQ	-.301121	.159342	[illegible]	[illegible]
MATHOFF	.061338	.027572	[illegible]	[illegible]
For ACDBKGD				
BASE	1.645439	.399137	[illegible]	[illegible]
AVSES	.671769	.347141	[illegible]	[illegible]
SECTOR	-.170281	.257070	[illegible]	[illegible]
HIMTYSCL	-.925654	.405714	[illegible]	[illegible]
MATHREQ	.355096	.126778	[illegible]	[illegible]
MATHOFF	.044680	.022549	[illegible]	[illegible]

THE PRECEEDING GAMMA(*) TABLE REFLECTS THE SPECIFIED WEIGHT[illegible]
THIS ANALYSIS WAS WEIGHTED USING TRINWT

THE CHI SQUARE TABLE:

PARAMETER	ESTIMATED PARAMETER VARIANCE	DEGREES OF FREEDOM	CHI SQUARE	P-VALUE
BASE	4.16260	[illegible]	[illegible]	[illegible]
MNRTY80 slope	2.46727	[illegible]	[illegible]	[illegible]
SES slope	.07547	[illegible]	[illegible]	[illegible]
ACDBKGD slope	.53932	[illegible]	[illegible]	[illegible]

Table 7-A: HLM Model of Minority Status, SES, and Academic Background [illegible] Achievement: Variation of Second-Stage Variables on [illegible] First-Stage Outcome.

Model: Stage 1: IRTMATH = MNRTY80 + SES + ACDBKRD
Stage 2a: (on Average Math Achievement):
BASE = SECTOR + AVSES + HIMTRYSCL + AVMTHEMP + [illegible]
Stage 2b: (on Minority/Achievement slope):
MNRTY/ACH = SECTOR + HIMTYSCL + DISCLIM
Stage 2c: (on SES/Achievement slope):
SES/ACH = SECTOR + AVSES + MATHOFF
Stage 2d: (on Academic Background/Achievement slope):
ACDBKRD/ACH = SECTOR + AVACDBGD + SDMTHEMP

THE GAMMA(*)-STANDARD ERROR-Z STATISTIC TABLE:

		GAMMA(*)	STANDARD ERROR	Z STATISTIC	P-VALUE
For	BASE				
	BASE	10.935327	2.033798	5.[illegible]	.000
	AVSES	2.476410	.527272	4.697	.007
	SECTOR	-.168799	.544027	-.310	.755
	HIMTYSCL	-1.883892	.692372	-2.721	.007
	AVMTHEMP	1.621446	.294599	5.504	.000
	AVLACKAC	-1.067842	.675778	-1.580	.114
	DISCLIM	-.494594	.256941	-1.925	.054
For	MNRTY80				
	BASE	-1.730249	.532465	-3.250	.002
	HIMTYSCL	1.998114	.745773	2.67[illegible]	.00[illegible]
	SECTOR	.218221	.397163	.24[illegible]	[illegible]
	DISCLIM	-.987549	.455234	-2.159	[illegible]
For	SES				
	BASE	.869231	.409862	[illegible]	[illegible]
	AVSES	1.953956	.386035	5.062	[illegible]
	SECTOR	-.181624	.299488	-.606	[illegible]
	MATHOFF	.051673	.025020	2.065	[illegible]
For	ACDBKGD				
	BASE	1.404763	.572270	2.455	[illegible]
	AVACBGD	1.717031	.333226	5.1[illegible]	[illegible]
	SECTOR	.003725	.249335	.0[illegible]	[illegible]
	SDMTHEMP	.931710	.386636	[illegible]	[illegible]

THE PRECEEDING GAMMA(*) TABLE REFLECTS THE SPECIFIED WEIGHTING.
THIS ANALYSIS WAS WEIGHTED USING TRIMWT

PARAMETER	ESTIMATED PARAMETER VARIANCE	DEGREES OF FREEDOM	CHI SQUARE	[illegible]
BASE	3.13021	1[illegible]1	[illegible]	[illegible]
MNRTY80 slope	1.35020	1[illegible]4	[illegible]	[illegible]
SES slope	.21442	[illegible]4	[illegible]	[illegible]
ACDBKGD slope	.41934	1[illegible]4	[illegible]	[illegible]

Table [illegible]-6: HLM Model of Minority Status, SES, and Academic [illegible] Course Enrollment: Unconditional Second Stage.

Model: Stage 1: MATHEMPH = MNRTY80 + SES + ACDBKGD
Stage 2: Unconditional 0[illegible]

THE GAMMA(*)-STANDARD ERROR-Z STATISTIC TABLE:

	GAMMA(*)	STANDARD ERROR	Z STATISTIC	P-VALUE
For BASE				
BASE	2.124694	.062426	34.034	.000
For MNRTY80				
BASE	.206012	.073341	2.809	.002
For SES				
BASE	.304464	.031159	9.771	.000
For ACDBKGD				
BASE	.527160	.023272	22.652	.000

THE PRECEEDING GAMMA(*) TABLE REFLECTS THE SPECIFIED WEIGHTING
THIS ANALYSIS WAS WEIGHTED USING TRIMWT

THE CHI SQUARE TABLE:

PARAMETER	ESTIMATED PARAMETER VARIANCE	DEGREES OF FREEDOM	CHI SQUARE	P-VALUE
BASE	.57672	116	1677.[illegible]	[illegible]
MNRTY80 slope	.31293	116	362.5[illegible]	[illegible]
SES slope	.06977	116	266.[illegible]	[illegible]
ACDBKGD slope	.04273	116	313.[illegible]	[illegible]

Table C 6: HLM Model of Minority Status, SES, and Academic Background on Math Course Enrollment: School Sector at Second Stage.

Model: Stage 1: MATHEMPH = MNRTY80 + SES + ACDBKGD
Stage 2: SECTOR

THE GAMMA(*)-STANDARD ERROR-Z STATISTIC TABLE:

	GAMMA(*)	STANDARD ERROR	Z STATISTIC	P-VALUE
For BASE				
BASE	1.602547	.073340	21.851	.000
SECTOR	1.106346	.106268	10.41[illegible]	.000
For MNRTY80				
BASE	.080997	.091036	.890	.374
SECTOR	.283004	.134017	[illegible]	.034
For SES				
BASE	.260890	.042543	6.132	.000
SECTOR	.090437	.062215	1.454	.145
For ACDBKGD				
BASE	.556880	.031864	17.477	.000
SECTOR	-.063586	.045932	-1.384	[illegible]

THE PRECEEDING GAMMA(*) TABLE REFLECTS THE SPECIFIED WEIGHTING
THIS ANALYSIS WAS WEIGHTED USING TRIMWT

THE CHI SQUARE TABLE:

PARAMETER	ESTIMATED PARAMETER VARIANCE	DEGREES OF FREEDOM	CHI SQUARE	P-VALUE
BASE	.40664	115	926.[illegible]4	[illegible]
MNRTY80 slope	.25827	115	[illegible]	[illegible]
SES slope	.06853	115	[illegible]	[illegible]
ACDBKGD slope	.04144	115	[illegible]	[illegible]

Table [illegible]-B: HLM Model of Minority Status, SES, and Academic Background on [illegible] Course Enrollment: School Sector and Average [illegible] Stage.

Model: Stage 1: MATHEMPH = MNRTY80 + SES + ACDBKGD
Stage 2: SECTOR + AVSES

THE GAMMA(*)-STANDARD ERROR-Z STATISTIC TABLE.

	GAMMA(*)	STANDARD ERROR	Z STATISTIC	P-VALUE
For BASE				
BASE	1.861226	.077051	24.155	[illegible]
AVSES	.711323	.131511	5.4[illegible]	[illegible]
SECTOR	.817840	.100430	[illegible]	[illegible]
For MNRTY80				
BASE	.026275	.1223[illegible]	[illegible]	[illegible]
AVSES	-.204109	.185090	[illegible]	[illegible]
SECTOR	.337266	.157114	[illegible]	[illegible]
For SES				
BASE	.453922	.050491	[illegible].330	[illegible]
AVSES	.505319	.083750	[illegible]	[illegible]
SECTOR	-.121901	.0662[illegible]	-1.8[illegible]	[illegible]
For ACDBKGD				
BASE	.60[illegible]796	.0396[illegible]	[illegible]	[illegible]
AVSES	.128925	.086061	[illegible]	[illegible]
SECTOR	-.122675	.0519[illegible]	[illegible]	[illegible]

THE PRECEEDING GAMMA(*) TABLE REFLECTS THE SPECIFIED WEIGHTING.
THIS ANALYSIS WAS WEIGHTED USING TRIMWT

THE CHI SQUARE TABLE:

PARAMETER	ESTIMATED PARAMETER VARIANCE	DEGREES OF FREEDOM	CHI SQUARE	P-VALUE
BASE	.25949	[illegible]4	[illegible]	[illegible]
MNRTY80 slope	.20045	[illegible]4	[illegible]	[illegible]
SES slope	.02556	[illegible]4	[illegible]	[illegible]
ACDBKGD slope	.02504	[illegible]4	[illegible]	[illegible]

Table 4-6. HLM Model of Minority Status, SES, [illegible] Course Enrollment of School Sector, [illegible] Minority Enrollment at Second Stage.

Model: Stage 1: MATHEMPH = MNRTY80 + SES + [illegible]
Stage 2: SECTOR + AVSES + HIMTYSCL

THE GAMMA(*)-STANDARD ERROR-Z STATISTIC TABLE.

	GAMMA(*)	STANDARD ERROR	[illegible]	[illegible]
For BASE				
BASE	1.876129	.074507	[illegible]	[illegible]
AVSES	.651965	.120547	[illegible]	[illegible]
SECTOR	.819467	.099539	[illegible]	[illegible]
HIMTYSCL	.382977	.170844	[illegible]	[illegible]
For MNRTY80				
BASE	-.011709	.125065	[illegible]	[illegible]
AVSES	-.083496	.197511	[illegible]	[illegible]
SECTOR	.334844	.158205	[illegible]	[illegible]
HIMTYSCL	.506654	.202853	[illegible]	[illegible]
For SES				
BASE	.450951	.051711	[illegible]	[illegible]
AVSES	.516876	.089050	5.804	[illegible]
SECTOR	-.123160	.067632	[illegible]	[illegible]
HIMTYSCL	.083326	.102371	[illegible]	[illegible]
For ACDBKGD				
BASE	.612792	.039589	[illegible]	[illegible]
AVSES	.068133	.068381	[illegible]	[illegible]
SECTOR	-.121975	.051571	[illegible]	[illegible]
HIMTYSCL	-.201542	.083030	[illegible]	[illegible]

THE PRECEEDING GAMMA(*) TABLE REFLECTS THE SPECIFIED WEIGHT[illegible]
THIS ANALYSIS WAS WEIGHTED USING TRIMWT

THE CHI SQUARE TABLE:

PARAMETER	ESTIMATED PARAMETER VARIANCE	DEGREES OF FREEDOM	[illegible]	[illegible]
BASE	.24427	[illegible]	[illegible]	[illegible]
MNRTY80 slope	.02175	[illegible]	[illegible]	[illegible]
SES slope	.02775	[illegible]	[illegible]	[illegible]
ACDBKGD slope	.00230	[illegible]	[illegible]	[illegible]