NATIONAL CENTER FOR EDUCATION STATISTICS

Working Paper Series

The Working Paper Series was created in order to preserve the information contained in these documents and to promote the sharing of valuable work experience and knowledge. However, these documents were prepared under different formats and did not undergo vigorous NCES publication review and editing prior to their inclusion in the series.

U. S. Department of Education
Office of Educational Research and Improvement

NATIONAL CENTER FOR EDUCATION STATISTICS

Working Paper Series

High School Curriculum Structure: Effects on Coursetaking and Achievement in Mathematics for High School Graduates

An Examination of Data from the National Education Longitudinal Study of 1988

Working Paper No. 98-09 August 1998

Contact: Jeffrey Owings
Schools and Families Longitudinal Studies Program, DDLSG
(202) 219-1777
email: jeffrey_owings@ed.gov

U. S. Department of Education
Office of Educational Research and Improvement

U.S. Department of Education
Richard W. Riley
Secretary

Office of Educational Research and Improvement
C. Kent McGuire
Assistant Secretary

National Center for Education Statistics
Pascal D. Forgione, Jr.
Commissioner

The National Center for Education Statistics (NCES) is the primary federal entity for collecting, analyzing, and reporting data related to education in the United States and other nations. It fulfills a congressional mandate to collect, collate, analyze, and report full and complete statistics on the condition of education in the United States; conduct and publish reports and specialized analyses of the meaning and significance of such statistics; assist state and local education agencies in improving their statistical systems; and review and report on education activities in foreign countries.

NCES activities are designed to address high priority education data needs; provide consistent, reliable, complete, and accurate indicators of education status and trends; and report timely, useful, and high quality data to the U.S. Department of Education, the Congress, the states, other education policymakers, practitioners, data users, and the general public.

We strive to make our products available in a variety of formats and in language that is appropriate to a variety of audiences. You, as our customer, are the best judge of our success in communicating information effectively. If you have any comments or suggestions about this or any other NCES product or report, we would like to hear from you. Please direct your comments to:

National Center for Education Statistics
Office of Educational Research and Improvement
U.S. Department of Education
555 New Jersey Avenue, NW
Washington, DC 20208

The NCES World Wide Web Home Page is
http://nces.ed.gov

Suggested Citation

U.S. Department of Education. National Center for Education Statistics. *High School Curriculum Structure: Effects on Coursetaking and Achievement in Mathematics for High School Graduates—An Examination of Data from the National Education Longitudinal Study of 1988*, Working Paper No. 98-09, by Valerie E. Lee, David T. Burkam, Todd Chow-Hoy, Becky A. Smerdon, and Douglas Geverdt. Jeffrey Owings, Project Officer. Washington, D.C.: 1998.

August 1998

Foreword

Each year a large number of written documents are generated by NCES staff and individuals commissioned by NCES which provide preliminary analyses of survey results and address technical, methodological, and evaluation issues. Even though they are not formally published, these documents reflect a tremendous amount of unique expertise, knowledge, and experience.

The ***Working Paper Series*** was created in order to preserve the information contained in these documents and to promote the sharing of valuable work experience and knowledge. However, these documents were prepared under different formats and did not undergo vigorous NCES publication review and editing prior to their inclusion in the series. Consequently, we encourage users of the series to consult the individual authors for citations.

To receive information about submitting manuscripts or obtaining copies of the series, please contact Ruth R. Harris at (202) 219-1831 (e-mail: ruth_harris@ed.gov) or U.S. Department of Education, Office of Educational Research and Improvement, National Center for Education Statistics, 555 New Jersey Ave., N.W., Room 400, Washington, D.C. 20208-5654.

Marilyn McMillen
Chief Statistician
Statistical Standards and Services Group

Samuel S. Peng
Director
Methodology, Training, and Customer
Service Program

This page intentionally left blank.

High School Curriculum Structure: Effects on Coursetaking and Achievement in Mathematics for High School Graduates

An Examination of Data from the National Education Longitudinal Study of 1988

Prepared by:

Valerie E. Lee, David T. Burkam, Todd Chow-Hoy,
Becky A. Smerdon, and Douglas Geverdt
University of Michigan

Prepared for:

U.S. Department of Education
Office of Educational Research and Development
National Center for Education Statistics

August 1998

The research that resulted in this study was supported by the School and Family Longitudinal Studies Program of the National Center for Educational Statistics (NCES), U.S. Department of Education, through a task order contract administered through MPR Associates, Berkeley, California. The data used in this study, the High School Effectiveness Supplement to the National Education Longitudinal Study of 1988, are available to researchers holding a license to use confidential data through NCES. The study's first author holds such a license (control number 912050011E). We appreciate assistance with the early part of the work from Karen Ross, as well as advice from NCES staff members Bob Burton and Jeffrey Owings, Director of the School and Family Longitudinal Studies Program, and from Ellen Bradburn of the Education Statistics Services Institute.

Preface

In this study, the authors investigated how the structure of the high school curriculum influences how far graduates get in the secondary mathematics course pipeline and their level of achievement in that subject by the end of high school. The study draws on data from the High School Effectiveness Supplement (HSES) of NELS:88, a broad-based longitudinal study of U.S. adolescents' experiences and accomplishments in public and private secondary schools in and around our nation's 30 largest cities, as well as from the students' high school transcripts. Data are available from the U.S. Department of Education through its National Center for Education Statistics. Using a two-stage stratified sample of 3,430 high school students in 184 high schools, the study used the Hierarchical Linear Models (HLM) statistical software to estimate school effects on individual students' behaviors and achievement.

The authors found that completing high-level mathematics courses is strongly associated with students' achievement. However, how schools structure their mathematics curricula influences how far their students get in the math course pipeline. Students who attend schools where more credits are accumulated in low-level mathematics courses make less progress to the more advanced courses. Curriculum structure—the types and numbers of mathematics courses offered and taken—has both a direct and an indirect effect on students' achievement in that subject. Implications of curriculum structure for students' academic progress are discussed.

Table of Contents

List of Figures

List of Tables

High School Curriculum Structure: Effects on Coursetaking and Achievement in Mathematics for High School Graduates

The publication of *A Nation at Risk* (National Commission on Excellence in Education 1983) jolted the public into critical scrutiny of the American high school. How best to organize a high school to maximize what its students actually learn increasingly has engaged policymakers, educators, and researchers since that time. These examinations have found wanting almost all aspects of high schools (for critiques, see Boyer 1983; Goodlad 1984; National Association of Secondary School Principals 1996; Powell, Farrar, & Cohen 1985; Sizer 1984, 1992). Furthermore, a consistent theme of these writings is a call for fundamental change in the structure of U.S. secondary schools.

The study described in this report focuses on an important feature of secondary schools: the curriculum. The study investigates how the structure of the high school curriculum influences the courses students take, how students' academic and social background characteristics are mapped onto their course choices, and ultimately how secondary school curriculum structure influences student achievement. The curriculum of high schools is organized around subject areas: English, foreign language, mathematics, science, social studies, and fine arts. Here we focus on curriculum and achievement in one subject only: mathematics. To maximize the influence of the curriculum on students' academic behavior and performance, we limit our study sample to students who stayed in high school for four years, until graduation.

Background

Conflicting Goals in the High School Curriculum

Any high school's curriculum reflects a formal codification of choices about what knowledge is deemed both worthy of transmission to younger generations and within the capacity of its students to master. Tensions between worth and appropriateness of knowledge embodied in the curriculum leads, in most high schools, to dual goals represented within its structure: differentiation and constraint. Balancing these two goals represents an attempt to form consensus around a set of common understandings and also to address individual differences in students' abilities and interests (Oakes, Gamoran, & Page 1992; Kleibard 1986). *Curriculum differentiation* reflects the diversification approach to this struggle. Here different knowledge is available to different groups of students, based on their aptitudes and tastes. This is part of an underlying dynamic that attaches distinct purposes and missions to the task of educating students within a single high school building. On the other side is a *constrained curriculum* approach, which promotes a belief about the appropriateness of a single set of academic goals for all participants. Under this approach, student choices and options are limited.

The high school curriculum can be constrained through limited opportunity as well as through proactive emphasis on moving students into and through a common set of experiences. Much of the research about this topic is framed within the "student choice" model: individual students choosing particular courses, and the influence of those choices on achievement. However, another research strand (mostly sociological in nature) has conceptualized the link between coursetaking and achievement as primarily a school, rather than a student, phenomenon. This model assumes that students partake in the curriculum of their school to the extent that it is available, and more subtly to the extent that they are encouraged to do so (Lantz & Smith 1981; Lee & Ekstrom 1987; Useem 1991). If the school offers a modest number of courses, largely academic in nature, these are the kinds of courses students take (Lee 1993). Thus, a constrained curriculum is evidenced both structurally, through the numbers of academic and non-academic options provided students, and behaviorally, through the actual variety of choices students make in carrying out their courses of study in high school.

Historical Background

The comprehensive high school. Before 1900, fewer than ten percent of 14 to 17 year olds were enrolled in secondary schools (Oakes 1985). Such schools were elite college-preparatory academies, with a narrow focus on a limited range of academic knowledge. In the first decades of the twentieth century, enrollment increased dramatically as more of this age group attended school and the U.S. population burgeoned through immigration. Both immigrant and migrant populations flocked to large cities; this movement was accompanied by economic and political shifts to restrict and finally to outlaw child labor (Cremin 1988). In response, secondary schools shifted their missions radically. Not all students who crossed the thresholds of public high schools planned to attend college, or even to stay in school for four years. As the types of students they were to educate diversified, the schools changed their goals and agendas.

Debates over what form the public high school curriculum should take polarized around two alternatives: (1) a common core of courses meant to be appropriate for all, or (2) a diversified set of offerings to accommodate the variety of students. As the debate settled in favor of the latter, the comprehensive high school was born (Conant 1959; Oakes 1985; Tyack 1974). By providing a wide array of options, “high schools would serve democracy by offering usable studies to everyone, rather than dwelling on academic abstractions that would interest only a few” (Powell, et al 1985, p.260). An important objective of the comprehensive curriculum has always been to keep students in school until graduation.

The constrained curriculum. Although similar demographic changes affected almost all high schools in the early years of this century, not all of them (especially non-public schools) abandoned a commitment to rigorous academic training (Kleibard 1986). Because most new immigrants were Catholic, the rapidly expanding Catholic educational system felt the need to accommodate its children. The same vigorous debate about the purposes and methods of high schools that had occurred among public school educators raged among those concerned with Catholic education. Issues of expansion, demographic shift, and curriculum focus were central to the debate among educators in both sectors, but the debate was resolved quite differently in the two settings. Settling on a rationale for a classical curriculum, the Catholic Church argued that developing a student’s ability to reason was “necessary in order to grasp fully the established understandings about person, society, and God. Although universal secondary education had expanded the base of people to be educated, the purpose of education should not change. Practical education deviated too far from the central moral aims of schooling” (Bryk, Lee, & Holland 1993, p. 31).

Even with rather similar student populations in public and Catholic secondary schools (particularly in the cities, where most Catholic schools have always been located), the high school curriculum in the two sectors diverged. Curriculum in the two sectors has always been based on fundamentally different views about what an appropriate secondary education should be. The comprehensive model currently dominates U.S. public high schools; the narrow academic curriculum still typifies Catholic schools. There are some basic disagreements among educators in the two sectors about whether social and intellectual differences among students are best addressed by diversifying instruction and content. The response to such diversity rests on basic differences about the ultimate aims of secondary education.

Much of the recent research investigating the structure of the high school curriculum has been formulated in cross-sector comparisons. However, one recent study pursued this issue only in public high schools (Lee, Croninger, & Smith 1997). The authors concluded that a constrained curriculum in mathematics has positive effects on high school achievement in that subject. In that study, “constrained curriculum” was measured in several ways: by students taking large numbers of academic courses in mathematics, by a high proportion of the school’s student body being in the college preparatory track, and by the proportion of the school’s total mathematics offerings that are academic. An important aspect of that study was its demonstration of considerable variation in curriculum structure in U.S. public schools. That finding undercuts potential critiques about the validity of cross-sector research that are based on potential selectivity bias as the logical explanation for the prevalence of the constrained curriculum in Catholic high schools.

<u>Curriculum reform in the 1980s</u>. The *Nation at Risk* report spurred some movement away from the diversified curriculum in public high schools in recent years. Efforts to upgrade the curriculum have been a major thrust of educational reform in the last decade, in the direction of more students taking more challenging courses (Clune & White 1992; McDonnell 1988; National Commission on Excellence in Education 1983). Taking academic courses has been identified as a primary determinant of achievement (Gamoran 1987; Jones, et al 1986; Lee & Bryk 1988). This association has provided empirical evidence consistent with this policy objective.

Two enduring educational aims motivate this type of reform of the high school curriculum: (1) U.S. students’ performance on standardized tests (excellence), and (2) unequal educational outcomes associated with students’ social backgrounds (equity). These concerns, and their social and economic implications, have helped shift the proportion of the curriculum that is academic back to levels that were common prior to the 1930s (Angus & Mirel 1995). There is evidence that such reforms, typically manifested by states and districts increasing graduation requirements, have resulted in students taking more academic courses. However, these reforms have not had the expected result of reducing student coursework in non-academic areas of the curriculum. Rather, students have taken *more* courses altogether (Clune & White 1992).

Unresolved issues regarding curriculum reform. Guided by the dual motivations of excellence and equity, reforms of the last decade have attempted to improve the high school curriculum and students' courses of study. However, fundamental normative issues underlie decisions about curriculum. For example, those who make decisions about curriculum might ask: "What courses should students take in high school?" "Should all students take the same courses?" "What courses should be offered and which should be dropped from the curriculum?" "What criteria should guide schools' decisions about what courses are offered and students' decisions about what courses are taken?" "Should schools guide students in choosing their course of study in high school, or should they leave the choice of courses to students and their families?" Although such questions are not addressed directly in this study, we hope that the results will provide empirical evidence to inform discussions and decisions about the high school curriculum.

A Conceptual Model for Studying Curriculum Effects

Cross-sector comparisons. Our conceptualization of the issue of how high school curriculum structure influences student achievement is rooted in research that compares Catholic and public schools. From the flurry of recent research comparing the effectiveness of schools in the two sectors, a consistent finding concerns the organization of the curriculum. One reason why Catholic school students achieve at higher levels than their public school counterparts, and why achievement there is also distributed more equitably among students of varying backgrounds is the difference in the academic organization of high schools in the two sectors (Bryk, et al 1993; Coleman, Hoffer, & Kilgore 1982; Lee 1985; Lee & Bryk 1988, 1989).

Virtually all students in Catholic high schools, regardless of race, social class, aspirations, or academic preparation, follow close to the same course of study: a narrow set of mostly academic offerings almost all of which are required. The courses that public school students take are more differentiated—they are allowed more choices, and their choices are more strongly associated with their backgrounds. Recent research, within the framework of school restructuring, has added empirical support for the associations between a school's academic organization and both effectiveness and equity (Lee & Smith 1995; Lee, Smith, & Croninger 1997).[1]

The mathematics curriculum. We decided to focus our study of curriculum and achievement on one subject: mathematics. Studies of the effects of tracking and grouping on student performance show the largest and most consistent effects in mathematics (Gamoran 1987; Lee & Bryk 1988). Mathematics is an area of the curriculum where learning is particularly responsive to school experiences (Murnane 1975). In this subject, in terms both of content and task expectations, performance measures more closely approximate the training that students receive in school than other school subjects.

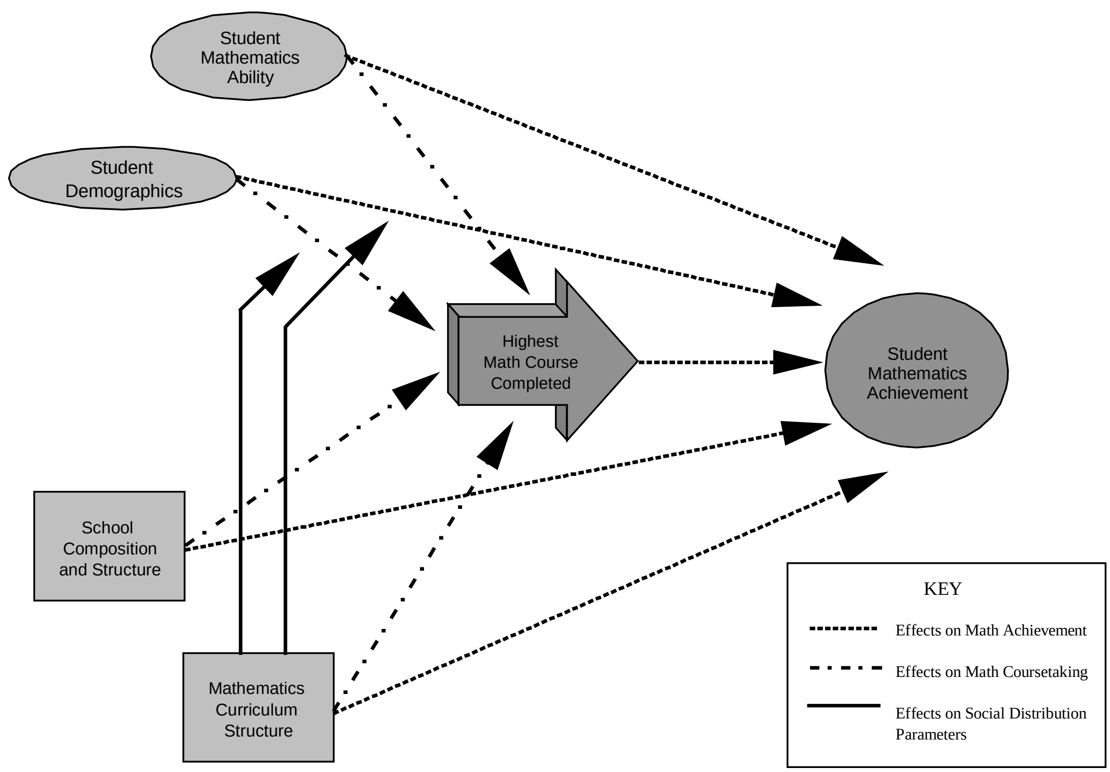
Explanations for this match include a more standardized secondary curriculum in mathematics than in other subjects, heavy reliance on a modest number of widely used texts, and traditional training of mathematics teachers (Romberg 1992). The close alignment between teaching and testing suggests mathematics as a fruitful subject in which to locate a study of the effect on achievement of course offerings, course selections, and other aspects of the structure of the high school curriculum.

In sum, we targeted this subject for several reasons: (1) its linear sequencing, (2) the ability to identify course content by course title (e.g., "Algebra II" has more specified content than "English II"); (3) the differentiation of the curriculum by course level; (4) the recognized importance of mathematical skills for college entry and a wide range of professions; and (5) the fact that it is learned almost entirely in school and not at home (Murnane 1975). A focus on mathematics allows study of the multi-dimensional nature of schools' influence on individuals' achievement: course offerings, school policies, course sequences, student coursetaking, and students' performance in school.

<u>The model</u>. Figure 1 presents the heuristic model that guided our investigation of the effects of curriculum structure on learning. The study's format is hierarchical; students are "nested" in high schools. Therefore, the model incorporates constructs of two types: those that describe *students* (their ability, their demographic characteristics, the courses they complete, and their achievement) and those that describe *schools* (their demographic composition, structural characteristics such as size and sector, and the structure of their mathematics curriculum).

Figure 1 takes the form of a multilevel path model. Characteristics of both students and schools are hypothesized to influence students' decisions about the mathematics courses taken in high school. We hypothesize that coursework, in turn, influences achievement. As described below, we operationalize the construct of coursework with the most advanced course in mathematics that students complete in high school. The path structure of our model means that we may test whether characteristics of students and schools have both a direct and an indirect effect on achievement, with the indirect effect mediated by the coursework students pursue.

Figure 1
Heuristic model for the effects of high-school curriculum structure on mathematics achievement



Source: U.S. Department of Education, National Center for Education Statistics, High School Effectiveness Study (HSES:90/92).

Another feature of the heuristic model shown in figure 1 is that we hypothesize that characteristics of schools (in particular the structure of the mathematics curriculum) influence not only coursework and achievement but also the social distribution of these outcomes. In this model we test whether coursetaking and achievement differ across high schools. Beyond differences between schools on those measures, we also investigate whether there is significant variation between schools in how coursework and achievement are distributed among students within schools according to their social characteristics (in this case, family socioeconomic status). As described below, this study makes use of a statistical methodology—Hierarchical Linear Models, or HLM—that capitalizes on the multilevel nature of the data and the hierarchical nature of the questions.

<u>The research questions</u>. Although there are several sets of relationships investigated in analyses suggested by figure 1, three major research questions drive this study. All three questions are multilevel, and for all three we take into account a substantial set of statistical controls (for students and schools).

> **Research question 1: Coursetaking**. How does the structure of high school mathematics curriculum influence the courses students complete in high school? In investigating this question, we take into account students' social and academic backgrounds, as well as the composition and structural characteristics of the schools they attend.
>
> **Research question 2: Achievement**. How does the structure of the high school curriculum affect students' achievement in mathematics at the end of high school? The analyses that address this question include controls for students' academic and social backgrounds, their high school courses of study, and the demographic and structural characteristics of their high schools.
>
> **Research question 3: Equitable distribution of coursetaking and achievement**. How does curriculum structure influence the relationship between students' socioeconomic status and both the courses they complete and their achievement? These analyses also include controls for other characteristics of students and schools.

For all three questions, we hypothesize that a more constrained mathematics curriculum, where more students complete the same set of high-level courses in that subject and schools offer fewer lower-level courses, is associated with higher levels of academic outcomes. That is, we hypothesize that a constrained curriculum results in students getting farther in the math course pipeline, in higher levels of achievement in mathematics, and in a more equitable social distribution of coursetaking and achievement.

Method

Data and Sample

The NELS:88 data. The sample used in this study was drawn from a data supplement to the first follow-up of the National Education Longitudinal Study of 1988 (NELS:88), sponsored by the National Center for Education Statistics [NCES] (Ingels, et al 1994). The purpose of NELS has been to document the educational status and progress of a nationally representative sample of U.S. secondary schools and their students. The NELS base year (1988) data collection was accomplished with a stratified design structure: schools were first sampled, and then a fixed number of students was sampled within each school. This resulted in a sample of about 25,000 eighth grade students in 1,035 American middle grade schools. The NELS design called for biennial data collection, with the same students followed into high school, where data were collected on them (and their schools) as high school sophomores (1990), seniors (1992), and two years after graduation (1994).

Base year data on NELS:88 students as eighth graders came from several sources: (1) a parent survey soliciting information on demographic and academic conditions of the home (usually provided by the mother); (2) a broad based survey of students' attitudes, behaviors, and aspirations relevant to education; (3) tests of students' achievement in mathematics, science, reading, and social studies; (4) data from two of their teachers (either English or social studies, and either mathematics or science); and (5) information describing schools from principals. Students, teachers, and parents also provided descriptive information about their schools.

The HSES data. The High School Effectiveness Study (HSES) is an independent, longitudinal survey executed within the NELS:88 data collection. Its purpose was to augment the original samples of students within high schools from the earlier NELS study, in order to make possible school effects studies (such as the one described here). Although it is a separate study, HSES borrows heavily from NELS:88, as it includes many of the same students and schools and follows a similar design. The data are selected through a complex, two-stage, stratified sample design, and NCES provides school weights to compensate for oversampling of certain types of schools (especially private schools and schools enrolling high proportions of minority students). Results of analyses using the HSES data set are therefore able to be generalized to the population of tenth to twelfth graders in urban and suburban secondary schools in the 30 largest metropolitan statistical areas (MSAs).

At the first step of the sampling, all high schools (urban or suburban schools in the 30 largest MSAs) enrolling one or more NELS:88 students at the first follow-up (1990) were selected (724 schools). A stratified sample of 276 schools from this pool was drawn, resulting in a final baseline sample of 247. The *High School Effectiveness Study Data File User's Manual* (Scott, et al 1996) provides complete details on the sampling strategies used for selecting schools and students. All NELS:88 first follow-up students attending the 247 schools in the HSES school sample were included in the HSES student sample.

The student sample was then augmented, using a sampling algorithm that took into account tenth grade enrollment of the HSES school. The original aim of the HSES was to produce a within-school cluster size of approximately 30 students. This has resulted in two distinct groups of students in each school: (1) those who were part of the original NELS sampling design, and (2) those who were added in the augmentation, having entered the sample only as tenth graders. As a result, the second group of students does not have data as eighth graders (i.e., before they entered high school). Thus, the HSES base year is 1990, when students were high school sophomores. Base year data for HSES come from the same sources as in NELS:88: students, parents, teachers, and administrators.

The analytic sample. Our investigation drew upon information about both students and schools, focusing on students who stay in school (and in the same school) through Grade 12. That is, we focused on high school graduates—those students with maximum exposure to their schools. We thus selected our sample in a two-stage fashion based on the availability of (1) student-level and (2) school-level data. Our analytic sample for this study was drawn from the available HSES sample of 7,642 students and 247 schools.[2] The analytic sample includes only those students with student questionnaires (S290QPFL) and complete tenth and twelfth grade mathematics test scores (S12XMIRR, S22XMIRR).[3] From the original sample, 5,449 students (and 238 schools) had tenth and twelfth grade questionnaire data available. Of those students with complete questionnaire data, 4,232 (and 230 schools) also had mathematics test scores both in 1990 and in 1992.[4]

Because our study focused on high school curriculum and student coursetaking, it was crucial that sampled students had complete transcript information available for Grades 9 through 12 (S2RTR09, S2RTR10, S2RTR11, S2RTR12). Employing this filter further reduced the sample to 3,741 students (and 213 schools). We selected only students with complete information on race (S1RACE), gender (S1SEX), and socioeconomic status, or SES (S2SES1), as we intended to include these important demographic characteristics in our multivariate models. These demographic selections reduced the sample to 3,724 students (and 213 schools).

After selecting students based on available student-level information, we turned our attention to key school characteristics. We first selected students from schools with administrative questionnaire data available at the two waves (S1ADMFLG, S2ADMFLG). This selection reduced our sample to 3,631 students and 207 schools. We chose to omit students in private schools that were neither Catholic nor members of the National Association of Independent Schools (NAIS),[5] because these “other” private schools were a non-homogeneous group with diverse purposes. Therefore, our school sample includes only public, Catholic, and NAIS schools (G10CTRL2). This selection resulted in a sample of 3,462 students and 198 schools.

Although not absolutely necessary for the HLM estimation procedure, we eliminated students in schools with less than five sampled students in them, a procedure we followed in other studies using NELS data (Lee & Smith 1995, 1997; Lee, Smith, & Croninger 1997).[6] This selection resulted in a final sample of 3,430 students in 184 schools. Thus, our final analytic sample represents 45 percent of the originally sampled HSES students and nearly 75 percent of the originally sampled HSES schools.

We investigated differences between the analytic sample of included students and schools and those students and schools eliminated from the HSES sample, the results of which are presented in appendix A. Although we recognize that the reductions in school and (especially) student sample sizes are substantial, we believe that the selection criteria were necessary in light of the purpose of our study. We note that the major loss of cases was a large number students who were nominally included in the sample due to HSES selection criteria, but who did not have questionnaire or test information, and thus were effectively "absent" from any useful analysis.

Weights. As with other longitudinal data collected under the sponsorship of NCES, analyses using the HSES data require the use of design weights to compensate for a stratified sampling strategy, unequal probabilities of selection, and to adjust for the effects of nonresponse. Both school-level and student-level weights are available on the HSES data file, and users must think carefully about selecting the appropriate combination of weights.

At the time we undertook this study, there were questions about the validity of the student-level weights included on the HSES file. For that reason, we chose not to weight our analyses at the student level for either descriptive or multivariate analyses. We did, however, employ the school level weight constructed with the "Qian-Frankel" probability model. We used the Qian-Frankel weight both for descriptive information on the schools and for the multivariate models. Appendix B includes an elaboration of the discussion about weights, the rationale for our choices, and the implications of those choices for our results. NCES will soon make available revised student-level weights with the HSES data files.

Measures

Outcomes. We employed two dependent variables in this study, mathematics achievement at the end of high school (twelfth grade) and highest mathematics course completed. Mathematics achievement was drawn from the twelfth grade NELS mathematics test. Unlike previous studies, our measure of mathematics coursetaking, drawn from student transcript data, represents *how far* students proceed through the mathematics pipeline (i.e., ranging from 1 = no mathematics through 8 = calculus), rather than the number of years they elect mathematics. This difference distinguishes our study from most other research on curriculum effects.

Appendix C provides details of the construction of all variables employed in this study.

Student background characteristics. Because one focus of this study is to investigate how socioeconomic status influences the outcomes, we included a measure of students' SES. We also drew on Oakes (1990) for our choice of other independent variables to use as covariates. Our covariates on students include: gender, minority status, and prior math achievement. The HSES sample only includes eighth grade test scores for the original NELS:88 core sample. This posed a serious measurement problem for this study, in that two-thirds of the analytic sample had no measure of student achievement and/or ability prior to high school (those students who "joined" the HSES sample at Grade 10). For this analysis we employed students' mathematics grade point average (GPA) in the ninth grade, taken from student transcript data, as a proxy for prior achievement.

School composition and structure. Curriculum structure is related to other characteristics of schools: school size is strongly related to the number of courses that a school can offer (Bryk, et al 1993; Lee & Smith 1995; Monk & Haller 1993), while average SES, minority enrollment, and school achievement levels similarly influence course offerings by affecting student interest and demand (Lee, Croninger, & Smith 1997). Therefore, we included several measures of school composition and structure as covariates: sector (i.e., public, Catholic, NAIS), school average social class, school size, minority concentration, proportion of low-achieving students, the average ninth grade mathematics GPA, and the variability of ninth grade mathematics GPA in each school.

Mathematics curriculum structure. The mathematics curriculum structure of American high schools, and its effects on achievement, is the primary focus of this study. Therefore, we included multiple measures to reflect curriculum structure. Two measures captured students' average progress through the mathematics curriculum: (1) the average of the highest course completed in each school, and (2) the variability of mathematics coursetaking in each school. The first, the school mean, estimates overall progress through the pipeline, or how far, on average, students go. The second measure—the within-school standard deviation [SD]—is an estimate of the uniformity of that progression, or how much disparity in coursetaking occurs. We designate schools with high average mathematics progress and low variability in mathematics coursetaking as "effective."

Other variables represented the availability and election of courses below algebra: (3) the number of mathematics courses offered below algebra in each school; (4) the average number of mathematics credits completed below algebra in each school; and (5) the variability (the within-school SD) in the number of mathematics credits completed below algebra in each school. The first measure captured the breadth of the low end of the mathematics offerings, the initial stages of the high school mathematics pipeline. The larger the number of low-level offerings, the greater the potential for certain students to remain at these early stages. The second two measures captured the actual coursetaking behavior in schools rather than the course offerings. Because students cannot elect what is not offered, another variable we employed focused on the high end of the mathematics curriculum: (6) whether or not calculus was offered in each school.

Analysis

Descriptive information. Our investigation proceeded from descriptive analyses of students and schools to multivariate causal models. The structural focus of all analyses was on the high school mathematics curriculum and students' progress through it. We began by investigating observed differences among students, differentiated by groupings that characterize their progress through the mathematics curriculum. Student demographics and achievement were compared for three such groups: (1) those whose total high school mathematics coursework was below the level of algebra [7.9 percent]; (2) those whose total high school mathematics coursework included or exceeded algebra, but was below the level of pre-calculus [57.4 percent]; and (3) those whose total high school mathematics coursework included pre-calculus or calculus [34.7 percent].

In addition to the large variation in mathematics progress *between individual students*, there is substantial variation in average student progress *between schools*. Consequently, we followed a similar strategy for describing the school sample. School demographics and curriculum structure were compared for three groups of schools, also differentiated by student progress through the mathematics curriculum: (1) those with low (more than one SD below the mean) average mathematics coursetaking [16.3 percent]; (2) those with middle (within one SD of the mean) average mathematics coursetaking [66.9 percent]; and (3) those with high (more than one SD above the mean) average mathematics coursetaking [16.8 percent].

A hierarchical approach. Since our research questions focused on estimating how the structure of the high school mathematics curriculum influenced how far students moved through it and their achievement in that subject, we used a method designed for such situations—Hierarchical Linear Modeling [HLM] (Bryk & Raudenbush 1992; Bryk, Raudenbush, & Congdon 1994). In an early school effects study using HLM, Lee and Bryk (1989) provided some methodological details within their application. HLM has also been used in other studies with designs similar to the study described here (e.g., Lee, Croninger, & Smith 1997; Lee & Smith 1993, 1995, 1996; Lee, Smith, & Croninger 1997). Readers interested in more details about HLM are referred to the studies cited in this paragraph, or to Appendix D, where we provide a brief overview of HLM as it is applied in this study.

The multivariate models in this study have a two-level hierarchical structure, with students nested in schools. There are three steps to a multilevel analysis of this type, which is often called a "school effects" study. In Step 1, the variance in the outcomes is partitioned into its within- and between-school components. It is only that proportion of the total variance that lies systematically between schools that may be modeled as a function of school factors. Step 2 involves the construction of a within-school (or Level-1) model. Here the outcome variable is modeled, separately in each school, as a function of the academic and social characteristics of the sampled students in that school. Step 3, the between-school (Level-2) model, investigates characteristics of schools that are related to the outcomes, which are school-level averages adjusted for the types of students in each school. It is Step 3 of an HLM model where school effects are identified.

The school effects model explored in this study. To pursue our research questions, we explored two different multilevel, multivariate models related to the mathematics curriculum and students' progress through the mathematics pipeline. The first model, which addresses Research Question 1, estimated the impact of the high school mathematics curriculum on students' progress through the mathematics pipeline. The dependent variable for this HLM model was the highest mathematics course completed. The Level-1 model here included controls for students' gender, minority status, SES, and ninth grade GPA in mathematics. The Level-2 HLM model for this outcome included school controls for composition and sector (e.g., average SES, proportion of low-achieving students, sector, size), and also the several variables that we have used to measure high school curriculum structure (e.g., number of courses the school offers below algebra, availability of calculus, average number of low-level mathematics credits completed).

The second set of HLM models, intended to explore Research Question 2, estimated the impact of the high school mathematics curriculum on students' twelfth-grade mathematics achievement. Student- and school-level controls were identical in the first and second models, except for the inclusion of students' individual mathematics progress (as an additional student-level predictor) and the school's average mathematics progress and variability in progress included as additional school-level predictors of achievement.

Level-2 predictors, which describe schools, were used to model outcomes that characterize both effectiveness and equity in U.S. secondary schools. The effectiveness of the school in the two models was investigated by estimating effects on the *intercepts* from the within-school models, which were represented by the adjusted school-level average of the highest mathematics course taken and mathematics achievement. Although equity issues in educational research may also focus on gender or minority status, in this study we restricted our equity focus to an investigation of the impact of the school mathematics curriculum on the social distribution of coursetaking and achievement. Specifically, we modeled the social class effects (the student-level SES slopes) on our two outcomes as functions of the school curriculum (slopes-as-outcomes). We characterize schools with an equitable social distribution of learning as having reduced SES effects on student pipeline progress and achievement.

Centering of independent variables in HLM. In all quantitative research, decisions about scaling and centering variables require careful consideration in order to interpret results appropriately. That is, researchers should ask themselves, "What does a value of zero on each variable actually mean?" This is especially important for slopes and intercepts of Level-1 HLM models for school effects studies, as these become outcomes in between-school investigations (Bryk & Raudenbush [1992] provide a technical discussion of centering in HLM). Decisions about where to center variables at Level 1 determine the exact nature of the outcome under investigation. The question each researcher needs to keep in mind is this: "What should the value of the within-school intercept represent?"

In multivariate models for this study, the continuous independent variables in our within-school models (SES and ninth grade math GPA) were first transformed into z-scores on our sample (mean [M] = 0, SD = 1). The other Level-1 predictors (minority status and gender) were dummy-coded. Further, all within-school predictors for our analyses (SES, gender, minority status, and math grades) were centered around their respective school means. This decision allowed us to model the distribution of adjusted school means (the intercepts) and school SES slopes in a meaningful way.[7] Because they do not serve as outcomes in HLM models, decisions about where to center Level-2 independent variables involve fewer technical concerns. Decisions here have substantive implications, however, because they influence interpretation of the school effects. Centering independent variables at the within-school level determines what is modeled; centering at the between-school level determines what the effects mean.

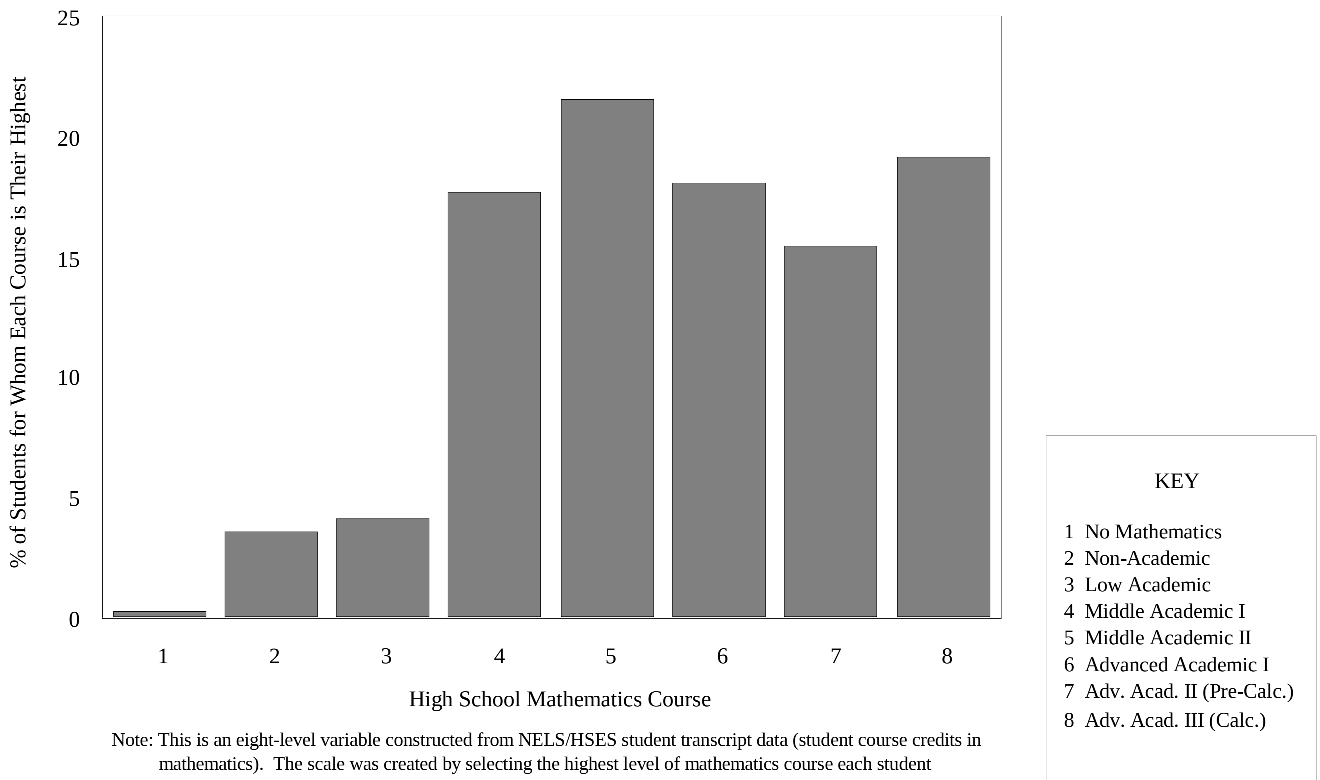
In our multivariate models, all continuous, Level-2 independent variables were normalized (i.e., SD = 1). The continuous measures of school social and academic composition (average SES, proportion of low-achieving students, minority concentration) were also transformed into z-scores (M = 0, SD = 1). However, the continuous curriculum structure measures (number of courses offered below algebra, average number of credits below algebra, variability in credits below algebra) were not transformed into z-scores, because in these cases a value of zero is "true." That is, a zero on these variables represents no courses offered below algebra or no credits completed below algebra. Of course, for dummy-coded Level-2 independent variables (e.g., whether the school offers calculus), zero also has substantive meaning.

Results

Who Progresses Through the Mathematics Pipeline? Descriptive Results

Highest mathematics course completed. The highest mathematics course completed in high school is not only a record of students' academic success, but it also serves as a filter for subsequent educational and vocational opportunities available to them (Hyde, Fennema, & Lamon 1990). Figure 2 displays the distribution of students' mathematics progress. Its negative skew indicates that few students who stay in high school until graduation remain at the low end. By the time they finish high school, only 8 percent of seniors in this sample had dropped out of the pipeline prior to completing a traditional Algebra I course (levels 1, 2, and 3 on this measure), the critical prerequisite for higher-level academic mathematics courses in high school. Even though there are small proportions of students at the very low end of the pipeline, over 50 percent of graduates stopped midway through the pipeline (levels 4, 5, and 6, including Algebra I, II, plane and analytic geometry). Over a third of seniors completed advanced mathematics courses (levels 7 and 8, pre-calculus and calculus), the critical prerequisites for college mathematics and science courses.

Figure 2
Highest mathematics course completed for high school graduates



Note: This is an eight-level variable constructed from NELS/HSES student transcript data (student course credits in mathematics). The scale was created by selecting the highest level of mathematics course each student completed with a passing grade during his/her four years in high school.

Source: U.S. Department of Education, National Center for Education Statistics, High School Effectiveness Study (HSES:90/92).

Differences between students. Which types of students remain at the low end of the pipeline? Which students proceed through the mathematics curriculum into the advanced mathematics courses? Virtually all research demonstrates that mathematics coursetaking, measured in years, is strongly related to students' background characteristics (see reviews by Hyde, et al 1990 and Oakes 1990). We also explored the relationship between student characteristics and mathematics coursetaking. We remind readers that the variable we use does not measure *years of coursework*, but rather *progress through the mathematics course pipeline*. Table 1 displays the characteristics of high school graduates who attain three levels of pipeline progress: (1) "low": below algebra, (2) "middle": algebra but below pre-calculus, and (3) "high": pre-calculus or calculus.

Table 1.--Group means of variables describing high school graduates, differentiated by the highest mathematics course completed

(n = 3,430 students in 184 schools)

Variable	**Below algebra (n = 271) Mean**	**Algebra but below pre-calculus (n = 1,969) Mean**	**Pre-calculus or calculus (n = 1,190) Mean**
Percent Female	44*[1]	51	44*
Percent Minority	42	37	17*
Black, Non-Hispanic	18	17	8*
Hispanic	21	19	9*
Asian	3*	8	17*
Social Class (SES)[2]	-.26* (.63)[3]	.14 (.78)	.70* (.71)
Mathematics GPA, Grade 9	1.66* (.90)	2.21 (.94)	3.04* (.84)
Mathematics Achievement, Grade 12	30.71* (8.41)	46.55 (12.40)	64.44* (9.53)
Highest Mathematics Course Completed	2.48* (.56)	5.01 (.79)	7.55* (.50)

*p<.05

1. For all variables, we tested two contrasts with one-way analysis of variance: Below Algebra (column 1) vs. Algebra but below Pre-Calculus (column 2), and Algebra but below Pre-Calculus (column 2) vs. Pre-Calculus or Calculus (column 3). Significance levels of the first contrast are included on means in column 1, and significance levels of the second contrast are included on means in column 3.
2. Social class is a z-score variable standardized on the full HSES sample.
3. SDs of continuous variables are in parentheses.

SOURCE: U.S. Department of Education, National Center for Education Statistics, *High School Effectiveness Study (HSES:90/92)*.

Gender differences in mathematics coursetaking are mixed. Although fewer girls complete pre-calculus or calculus than boys (44 percent of the students in this group are females), girls are also less likely to end their mathematics coursetaking with non-academic or low-level courses (i.e., below Algebra I). More girls than boys stop taking math courses midway through the pipeline, whereas boys typically either stop early or make it to the end of the pipeline {t = 2.42, t = 4.04, respectively}.

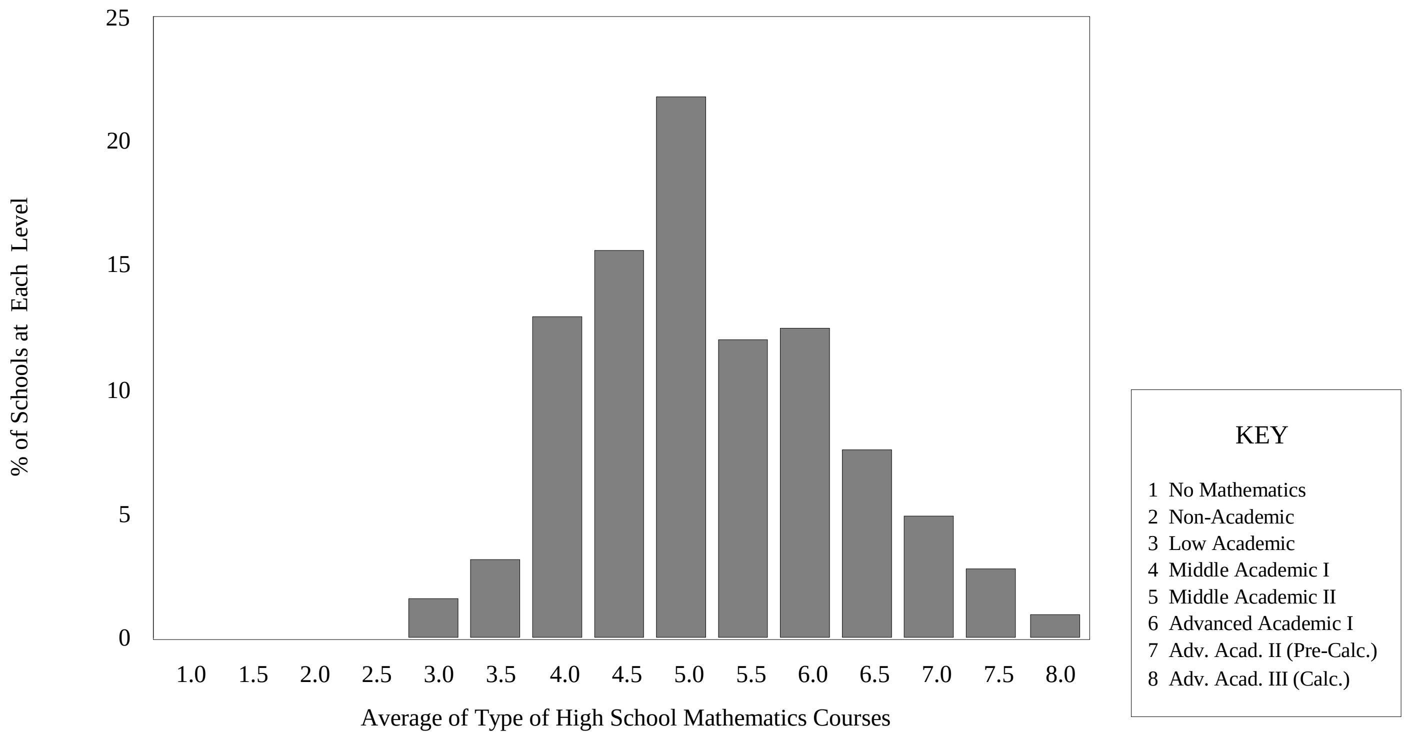
Disparities by social class and race/ethnicity are large, and they follow a common pattern. Seventeen percent of the students who reach the end of the mathematics pipeline are minority students, whereas nearly half (42 percent) of those at low levels are minority {t = 8.18}. This is the pattern for black and Hispanic students {t = 6.69, 6 = 5.01, respectively}; Asian students do not follow this pattern: although 17 percent of students taking pre-calculus or calculus are Asian, 3 percent of those who end with the low-level mathematics courses are Asian {t = 7.29}. Social class (SES) is also strongly related to pipeline progress: high-SES students move further. Students in the low group have much lower average SES than those in the middle group (effect size [ES] = .40 for the group difference, t = 8.24).[8] The largest difference is between students who dropped out of the pipeline early and those who proceeded to the end (ES = .96, t = 19.22).

Students' academic status and progress, measured by mathematics grades in ninth grade and achievement near the end of twelfth grade, are strongly related to their progression through the pipeline. Students who completed higher-level mathematics courses received substantially higher mathematics grades in their first year of high school (GPA = 3.04) and displayed less variability in GPA (SD = .84) than their counterparts who did not take algebra (GPA = 1.66, SD = .90, t = 22.24 and F = 16.91). Further, these students exhibited substantially higher mathematics achievement in their final year of high school (64.44 vs. 30.71, ES = 3.54 SD, t = 44.75). The SES and performance of students remaining midway through the pipeline is more variable than the groups at either extreme {F = 15.84 and F = 99.07, respectively}.

<u>School Factors Associated With Greater Student Progress in the Mathematics Curriculum: Descriptive Results</u>

<u>High- vs. low-progress schools</u>. Although the distribution of students' progress through the mathematics pipeline is negatively skewed, the distribution of school average progress is close to normally distributed (see figure 3). Across all schools, the average progress ranges from a low near three (a school where the average progress leaves students below algebra) to a high of eight (a school where _all_ students reach calculus).[9] We characterize high-progress schools as those where average student progress through the mathematics pipeline is more than one SD above the mean of this variable across schools; low-progress schools are those in which average student progress is more than one SD below the mean. Because this variable is close to normally distributed, a third of all schools fall in either of these two categories, with as many schools of high as of low progress.

Figure 3
School average of highest mathematics course completed for high school graduates



Note: This is an eight-level variable constructed from NELS/HSES student transcript data (student course credits in mathematics). The scale was created by selecting the highest level of mathematics course each student completed with a passing grade during his/her four years in high school. The school average was computed and rounded to the nearest .5.

Source: U.S. Department of Education, National Center for Education Statistics, High School Effectiveness Study (HSES:90/92).

What distinguishes schools with different levels of average progress in the mathematics course pipeline? Table 2 presents information on school composition and structure, mathematics curriculum structure, and average school achievement for three groups of schools: (1) schools of low average progress [ranging from 3.0 to 4.43; 15.8 percent of the schools]; (2) schools of middle average progress [ranging from 4.43 to 6.5; 66.8 percent of the schools]; (3) schools of high average progress [ranging from 6.5 to 8.0; 17.4 percent of the sample].

Differences between schools. School composition and structure. Descriptive differences between the school groups in table 2 appear to be larger than those between the groups of students shown in table 1. Consistent with individual predictors of progress, high average levels of pipeline progress are associated with low-minority and high-SES enrollments, and fewer low-achieving students. Conversely, three fourths of the low-progress schools have high minority enrollments (40 percent or more minority students), and, on average, nearly half of the students in low-progress schools earned a C or below in ninth grade mathematics. There are also differences by school sector: all of the low-progress schools are public schools; 14 percent of the high-progress schools are public schools {t = 6.48}. These findings are consistent with other research that has shown large differences in academic coursetaking between students in public and Catholic schools (e.g., Bryk, et al 1993; Lee & Bryk 1988). High-progress schools are also substantially smaller, on average {t = 5.11}, a structural feature associated with school sector.

Table 2.--Group means of variables describing high schools, differentiated by the school average of students' highest mathematics course completed

(n = 184 schools)

Variable	Low average coursetaking (n = 30)	Middle average coursetaking (n = 123)	High average coursetaking (n = 31)
A. School composition			
Percent high minority schools	75*[1]	23	4*
Percent of low-achieving students	47*	29	26
Average SES	-.26* (.36)[2]	.23 (.40)	.83* (.22)
B. School structure			
Percent Catholic schools	0	13	55*
Percent NAIS schools	0	2	31*
School size	1426 (785)	1300 (748)	649* (425)
C. Structure of mathematics curriculum			
Percent offering calculus	45*	83	100*
Mean, number of courses offered below algebra	4.63 (.82)	4.14 (1.55)	2.11* (1.92)
Mean, credits taken below algebra	1.21* (.44)	68 (.40)	.09* (.11)
SD, credits taken below algebra	.96*	.82	.24*
D. Student Achievement			
Mean, math GPA, grade 9	1.96* (.29)	2.38 (.40)	2.64* (.30)
SD, math GPA, grade 9	.93	.96	.98
Mean, math achievement, grade 12	40.42* (5.15)	50.46 (6.59)	58.41* (5.33)
SD, math achievement, grade 12	13.13*	12.03	12.15
Mean, highest math course completed	4.08* (.35)	5.42 (.54)	7.21* (.57)
SD, highest math course completed	1.35	1.39	.81*

p<.05

1. For all variables, we tested two contrasts with one-way analysis of variance: Low Average Coursetaking (column 1) vs. Middle Average Coursetaking (column 2), and Middle Average Coursetaking (column 2) vs. High Average Coursetaking (column 3). Significance levels of the first contrasts are included on the means in column 1, and significance levels of the second contrast are included on the means in column 3.
2. SDs of continuous variables are in parentheses.

SOURCE: U.S. Department of Education, National Center for Education Statistics, *High School Effectiveness Study (HSES:90/92)*.

Curriculum structure. It is expected that average coursetaking reflects curriculum structure. All of the high-progress schools offer calculus (a necessity for students to elect it) but less than half of the low-progress schools offer this course. Although not offering calculus prevents students from taking the course, it may also be a reasonable omission for schools in which there is little demand for the course.

Low- and middle-progress schools offer nearly twice as many math courses below algebra as high-progress schools. Furthermore, low-progress schools more consistently offer a larger number of such courses (the SD of the means = .82), while high-progress schools—those that offer fewer such courses on average—display much more variability (SD of the means = 1.92, F = 17.00). Although low- and middle-progress schools offer similar numbers of these courses, students in low-progress schools complete more low-level coursework than students in middle-progress schools (average number of credits per student: 1.2 vs. 0.7, t = 6.73).[10] Almost no students in high-progress schools complete coursework below the level of algebra (average number of credits per student: .09).

Students in low-progress schools display substantially more variability in low-level coursetaking than students in high-progress schools {F = 10.63}. In low-progress schools, many students take additional credits below algebra, while other students in the same school are taking no credits below algebra (these bimodal distributions result in the larger average SD for low-progress schools [.96]). High-progress schools display the least variability in low-level mathematics coursetaking: in the typical high-progress school, very few per-pupil credits below algebra are completed (M = .09), and high-progress schools consistently display this pattern (SD of the means = .11). Furthermore, students within the high-progress schools are more similar in their coursetaking behavior (average SD = .24, t = 11.8).[11]

School achievement. The achievement-related antecedents and results of high progress in schools are clear and consistent. On average, students in high-progress schools did better in their ninth grade math courses (GPA = 2.6, or a B-) than students in low-progress schools (GPA = 2.0, or a C, t = 7.37), although all schools (low-, middle-, and high-progress schools) display similar within-school variability in grades. Twelfth-grade mathematics achievement is over 40 percent higher in high- than low-progress schools (58.4 vs. 40.4; a difference of ES = 1.09 SD, t = 11.59).

Summary of descriptive differences. On virtually every variable we considered in our multivariate models, both between students and between schools, there were statistically significant differences related to students' progress through the mathematics pipeline. Group differences among students were associated with social background (SES, race/ethnicity) and academic performance at both the beginning and end of high school. There were also differences in average pipeline progress by school sector, by school size, and by the structure of the high school curriculum. Although these differences suggest curriculum structure effects on student achievement, it is important to remember that the mean differences displayed in tables 1 and 2 are descriptive—they do not take other characteristics of students and schools into account. We know that many of the variables we consider here are correlated. Thus, we investigate these questions within a multivariate format. As we discussed, it is also appropriate to consider these questions within a multilevel format. We move to these analyses now.

Multivariate and Multilevel Analyses

Unconditional HLM models. Table 3 displays the psychometric properties of the two outcome variables in this study: the highest mathematics course completed and mathematics achievement at twelfth grade. These results were computed as fully-unconditional HLM models of the two outcomes. Two statistics are especially useful here. First, we see that each of these outcomes demonstrated moderately high (and quite similar) lambda reliability (.770 for coursework; .719 for mathematics achievement). As school effects may be estimated only on the proportion of variability in the outcome that is systematically between schools, the intraclass correlation (ICC) is also informative. The estimated ICCs here were relatively high. Over two-fifths of the total variance in the measure of highest course completed (41.3 percent) lay between schools. Although not quite so high, more than one-third (35.2 percent) of the total variance in twelfth-grade mathematics achievement was between schools. These ICCs are somewhat higher than those in similar studies investigating the effects of the high school curriculum on student achievement (Lee & Bryk 1989; Lee & Smith 1995; Lee, Croninger, & Smith 1997). The relatively high ICCs of these outcomes, combined with their moderately high reliabilities, indicate the likely presence of school effects.

Table 3.--HLM psychometric properties of student outcomes: Highest mathematics course completed and mathematics achievement in grade 12[1]

(n = 3,430 students in 184 schools)

	Model 1 Highest Mathematics Course Completed	**Model 2** Mathematics Achievement
Pooled Within-School Variance (Sigma-Squared)	.592	.685
Between-School Variance (Tau)	.321	.267
Within-School SD [2]	.769	.828
Between-School SD [2]	.567	.753
Reliability (Lambda)	.770	.719
Intraclass Correlation, Unadjusted (ICC)[3]	.352	.280
Intraclass Correlation, Adjusted (ICC)[3]	.413	.352

1. Outcome variables are in a z-score metric (M=0, SD=1) for this and other HLM analyses.
2. The within-school SD is the square root of sigma-squared; the between-school SD is the square root of Tau.
3. Unadjusted ICC = Tau /(Tau + Sigma; Adjusted ICC = Tau /(Tau)+(Sigma * Lambda).

SOURCE: U.S. Department of Education, National Center for Education Statistics, *High School Effectiveness Study (HSES:90/92)*.

Within-school HLM models. Table 4 displays three within-school (Level 1) HLM models. Each model is similar, in that it has a similar set of independent variables. Because all variables included in these models were either z-scored or dummy-coded, the beta coefficients shown in table 4 are in an effect-size (SD) metric (see technical note 8). Using effect sizes allows us to interpret effects both substantively and statistically. (nominal significance levels are indicated by p-values). Model 1 of table 4 displays results for our within-school analysis of the highest mathematics course completed; Model 2 displays similar results for mathematics achievement. What distinguishes Models 2A and 2B is that the highest mathematics course completed is included in the within-school HLM in Model 2B but not in Model 2A. In these models, the intercept and SES slopes become outcomes in our between-school HLM models to follow.

Table 4.--Within-school HLM models of highest mathematics course completed and mathematics achievement in grade 12

(n = 3,430 students in 184 schools)

Variable	**Model 1** Highest mathematics course completed β Coefficient	**Model 2A** Mathematics achievement without coursetaking β Coefficient	**Model 2B** Mathematics achievement with coursetaking β Coefficient
Intercept(β_0)	-.066	-.057	-.064
Social Class (SES)(β_1)	.194*	.166*	.034
Gender (Female)(β_2)	-.055*	-.179*	-.141*
Minority Status(β_3)	-.046	-.333*	-.305*
Mathematics GPA, (β_4) Grade 9	.310*	.338*	.131*
Highest Mathematics (β_5) Course Completed			.658*

The Chi-Square Table

Parameter	Estimated parameter	Degrees of variance(Tau)	Chi-square freedom
Highest math course			
Intercept	.332	183	2855*
SES slope	.027	183	231*
Mathematics achievement (Without coursetaking)			
Intercept	.290	183	2551*
SES slope	.034	183	215*
(With coursetaking)			
Intercept	.326	183	4233*
SES Slope	.031	183	212

*p<.05

SOURCE: U.S. Department of Education, National Center for Education Statistics, *High School Effectiveness Study (HSES:90/92)*.

Model 1. Both SES and ninth grade mathematics GPA are positively and significantly related to mathematics course pipeline progress, although the magnitudes of effects are small for SES (Þ = .194, t = 7.85) and moderate for GPA (Þ = .310, t = 23.36). Gender has a significant effect that is quite small (Þ = -.055, t = -1.97); on average, girls are slightly less advanced in the pipeline. In this multivariate within-school HLM model, minority status is unrelated to progress in the mathematics pipeline {t = -1.25}. The chi-square statistics at the bottom of table 4 indicate that both average progress (the intercept, Þ0) and its relationship with SES within schools (the slope, Þ1) varies significantly between schools. This suggests that they are appropriate for modeling as outcomes in between-school HLMs.

Model 2. All measures of students' demographic and academic background are significantly related to achievement in mathematics at the end of high school, as shown in Model 2A. Minority students and girls have lower achievement in mathematics; students from higher-SES families and those with higher math grades in ninth grade achieve at higher levels _{t = 6.19 and t = 24.22, respectively}. The magnitude of the SES and gender effects is small; the effects for minority status and math GPA are of moderate magnitude. However, once students' coursework in mathematics is taken into account (Model 2B), the SES effect drops to non-significance {t = 1.48} and the influence of math GPA is more than halved (from .338 to .131, t = 11.07).[12] Minority and gender effects on achievement are relatively unchanged between Models 2A and 2B (i.e., the achievement gaps between male and female students, and between minority and majority students) are unaffected by their progress in the mathematics pipeline {t = -16.10 and t = -6.21 respectively}. Students' progress in the mathematics coursework pipeline is strongly related to achievement in this multivariate model (Þ = .658, t = 45.74).

Regardless of social background and students' academic status at the beginning of high school, and regardless of the high school they attend, students' achievement in mathematics is strongly influenced by how far in the math pipeline they get.[13] In this subject, students achieve at higher levels when they take more advanced courses. Of course, students' progress in the pipeline is itself a function of their social and academic backgrounds (as seen in Model 1 of table 4). As our model in figure 1 suggests, students' demographic characteristics and their ability at the beginning of high school have both direct and indirect effects on achievement; the indirect effects "pass through" the courses students take during their high school career. A major objective here, however, is to investigate how the structure of the high school mathematics curriculum influences achievement. To pursue this question, we turn to our Level-2 HLM school effects models.

Between-school HLM models. Results of our investigation of curriculum structure effects on students' progress in the mathematics pipeline are displayed in table 5 (Model 3). As we explained earlier, this analysis includes the within-school model on this outcome shown in Model 1 of table 4. We investigate two outcomes here: (1) the adjusted school average of the highest math course students complete (Þ0) and (2) the relationship between SES and coursework (Þ1). We interpret these two outcomes as measures of effectiveness and equity.

Two types of school effects are considered: (1) school composition and structure (which we use to control for academic and social differences among schools) and (2) curriculum structure. The emphasis here is on the latter. We began the modeling process with a full set of controls for school selectivity (average SES, school minority concentration, the proportion of low-achieving students in the school, school size, and school sector) on both the effectiveness and equity outcomes. However, in the models displayed in table 5 we dropped several control variables due to non-significance. We followed a rule favoring model parsimony to maximize the stability of our HLM analyses (although in each model we retained a full and identical set of curriculum structure measures).

Table 5.--Between-school HLM model of highest mathematics course completed

(n = 3,430 students in 184 schools)

	Model 3 Highest Mathematics Course Completed
	γ Coefficient
<u>Random effects</u>	
Intercept (β_0)	
Intercept	.041
<u>Composition and structure</u>	
Average SES	.163*
Proportion of low-achieving students	-.125*
Catholic school	.107
NAIS school	.275*
<u>Curriculum structure</u>	
Courses offered below algebra	-.041
Mean, credits taken below algebra	-.258*
SD, credits taken below algebra	.020
Calculus offered	.243*
SES/coursetaking slope (β_1)	
Intercept	.026
<u>Composition and structure</u>	
Average SES	.076*
<u>Curriculum structure</u>	
Courses offered below algebra	-.002
Mean, credits taken below algebra	-.017
SD, credits taken below algebra	.102*
Calculus offered	-.016
<u>Fixed Effects</u>	
Gender (female) (β_2)	-.056*
Minority status (β_3)	-.034
Mathematics GPA, grade 9 (β_4)	.310*

The Chi-Square Table

Parameter	Estimated Parameter Variance (Tau)	Degrees of Freedom	Chi-Square
Intercept	.075	175	640*
SES/Coursetaking Slope	.021	178	209

*p<.05

Note: Minority concentration and size were dropped from the intercept model. Minority concentration, size, sector, and proportion of low-achieving students were dropped from the SES/Coursetaking slope model.

SOURCE: U.S. Department of Education, National Center for Education Statistics, *High School Effectiveness Study (HSES:90/92)*.

Average pipeline progress. Students move farther in the mathematics pipeline if they attend schools with higher average SES and fewer low-performing students {t = 3.56 and t = -3.87 respectively}. Although there were large observed sector differences shown in table 2, in these multivariate and multilevel models differences in pipeline progress between public and Catholic schools are small and non-significant {t = 1.19}. However, students in NAIS schools move significantly farther in the mathematics course pipeline than their public school counterparts (gamma = .275, t = 2.23). Sector differences in pipeline progress all but disappear once differences in factors such as curriculum structure are taken into account. The effects of curriculum structure are evident in this model. On average, the level of students' progress in the mathematics course pipeline is lower when the school's students take more low-level courses (those below algebra, t = 5.27).[14] On average, students move farther in the mathematics course pipeline when calculus is available in the school.

There are few school effects on the SES/coursetaking slope. Coursetaking is less equitably distributed in higher-SES schools (gamma = .076, t = 2.20). Schools are also less equitable if the variability in low-level courses taken is higher (recall that positive effects increase the SES slope, which measures increased inequity, t = 2.45). However, in schools that offer no low-level courses (and hence students complete no low-level coursework), there is no significant social inequity (gamma = -.026, t = 0.28). Although measures of curriculum structure influence the intercept (itself a mean), a distributional measure (the SD of low-level credits) had an effect on the social distribution outcome. Fixed effects in this model (gender, minority status, and mathematics ability) are very similar to those shown in table 4.

How well has this school-effects model explained variance in average pipeline progress and the SES slope? We estimated this by comparing the taus from the within-school models (in table 4) to the taus shown in the bottom panel of table 5. For the school average of the highest mathematics course completed, 77.4 percent of the between-school parameter variance has been explained [(.332 - .075)/ .332]. For the social distribution of pipeline progress, however, the model explained 22.2 percent of the variance. The difference in proportions of variance explained for the two outcomes is attributable, at least in part, to the fact that slopes are generally estimated with considerably lower reliability (see technical note 14).

Average mathematics achievement. The between-school HLM models with mathematics achievement as an outcome are shown in table 6. The within- school model is identical to that shown in Model 2B of table 4, where students' progress in the mathematics course pipeline is included as a control. Along with gender, minority status, and ninth grade math GPA, this variable is estimated as a fixed effect. Again, the four fixed effects are virtually unchanged between Level-1 (table 4) and Level-2 models (table 6).[15] The distinction between Models 4A and 4B relates to the variability in coursetaking. Model 4A includes the four curriculum structure variables we included in Model 3 of table 5, whereas Model 4B adds the school average of the highest mathematics course completed and the standard deviation of that measure to the existing set of curriculum structure measures.

Table 6.--Between-school HLM models of mathematics achievement in grade 12
(n = 3,430 students in 184 schools)

	Model 4A Mathematics Achievement Without Aggregate School Coursetaking	**Model 4B** Mathematics Achievement With Aggregate School Coursetaking
	γ Coefficient	γ Coefficient
<u>Random Effects</u>		
Intercept (β_0)		
Intercept	-.001	-.001
<u>Composition and Structure</u>		
Average SES	.358*	.281*
Proportion of Low-Achieving Students	-.125*	-.088*
<u>Curriculum Structure</u>		
Courses Offered Below Algebra	-.027	-.017
Mean, Credits Taken Below Algebra	-.101*	.002
SD, Credits Taken Below Algebra	-.003	-.024
Calculus Offered	.114	-.023
Mean, Highest Mathematics Course Completed		.240*
SD, Highest Mathematics Course Completed		.081*
SES/Mathematics Achievement Slope (β_1)		
Intercept	-.049	-.152
<u>Composition and Structure</u>		
Average SES	.023	-.004
<u>Curriculum Structure</u>		
Courses Offered Below Algebra	-.016	-.005
Mean, Credits Taken Below Algebra	-.031	-.003
SD, Credits Taken Below Algebra	.086*	.110*
Calculus Offered	-.017	-.020
Mean, Highest Mathematics Course Completed		.073
SD, Highest Mathematics Course Completed		-.026
<u>Fixed Effects</u>		
Gender (Female) (β_2)	-.141*	-.141*
Minority Status (β_3)	-.303*	-.302*
Mathematics GPA, Grade 9 (β_4)	.131*	.131*
Highest Mathematics Course Taken (β_5)	.656*	.658*

SOURCE: U.S. Department of Education, National Center for Education Statistics, *High School Effectiveness Study (HSES:90/92)*.

Table 6.--Between-school HLM models of mathematics achievement in grade 12--Continued

Chi-Square Table

Parameter	Estimated parameter variance (Tau)	Degrees of freedom	Chi-square
Without Coursetaking, Model 4A			
Intercept	.077	177	1048*
SES/Achievement Slope	.031	178	208
With Coursetaking, Model 4B			
Intercept	.067	175	924*
SES/Achievement Slope	.028	176	217*

*p<.05

Note: Minority concentration, size, and sector were dropped from the intercept model. Minority concentration, size, sector, and proportion of low-achieving students were dropped from the SES/Achievement slope model.

SOURCE: U.S. Department of Education, National Center for Education Statistics, *High School Effectiveness Study (HSES:90/92)*.

In both Models 4A and 4B, mathematics achievement is higher in schools with higher average SES and with a lower proportion of low-achieving students. With curriculum structure taken into account, we again dropped non-significant measures of school composition and structure (minority concentration, school sector, school size). Comparing effects of curriculum structure on average mathematics achievement in Models 4A and 4B, we see that average pipeline progress, and its variability, are strongly and significantly related to achievement. When average pipeline progress is not taken into account (Model 4A), achievement is lower in schools where the mean number of credits of low-level courses is higher. Though pipeline progress is related to calculus being offered (Model 3, table 5), here whether or not calculus is offered is unrelated to achievement.

Thus, schools' average achievement levels are higher when, on average, their students move farther in the mathematics course pipeline, but also when there is more variability in this pipeline measure within the school. There are few curriculum structure effects on the social distribution of mathematics achievement by SES. In Models 4A and 4B, variability in low-level coursetaking (i.e., average credits taken below algebra) is positively related to the SES/achievement slope. More variability in low-level coursetaking fosters a more inequitable social distribution of achievement in high schools. Although they are strongly related to average achievement (effectiveness), the two measures of pipeline progress are unrelated to the distribution of achievement within schools (equity).

The two between-school models shown in table 6 have explained over three fourths of the between-school variance in mathematics achievement: 76.6 percent for Model 4A; 79.4 percent for Model 4B. However, the proportion of total variance in the SES/achievement slopes is only slightly affected by these between-school models (i.e., only 9.7 percent has been explained in Model 4B).

Discussion

Summary of Findings

Observed differences. The number and type of mathematics courses offered and taken in high school are associated with many characteristics of students and schools. In our descriptive analyses, several background characteristics were associated with less progress in the curriculum (being black or Hispanic, being from a lower-SES family, earning lower math grades early in high school, being female). A similar pattern was found for high school curriculum structure. Schools with more minority students, with lower average SES, and with more low-achieving students demonstrate less average progress through the mathematics course pipeline. Average progress also differed by the school structural characteristics of sector (private schools show more progress) and size (students in smaller schools make more progress). However, these analyses did not take account of interrelationships between various background characteristics.

All of the students in this sample stayed in high school until graduation. Comparisons of HSES students who were included and excluded in this study (appendix A) show the excluded sample to be disadvantaged in several respects (e.g., lower SES, lower grades in ninth grade—see appendix table A-1). Those comparisons provide evidence to suggest that the association between background and coursetaking in this study would be even larger if our sample included students who dropped out of high school. Thus, our estimates of such social stratification in these outcomes probably represent a lower bound for the full high school population.

<u>Determinants of students' progress through the high school mathematics curriculum</u>. Individual students' achievement in mathematics is associated strongly with their progress through the mathematics curriculum. Even in multivariate models which take account of students' social background and academic status at the beginning of high school, students' progress in the mathematics course pipeline is the strongest single predictor of their achievement—twice the strength of any other factor.

The association between coursetaking and achievement demonstrated in other research motivated our attempts to identify its determinants. In particular, we wanted to know whether the number and type of courses the school offers influences how far through the standard academic mathematics sequence students get, and ultimately how both these factors influence achievement. Thus, the focus of this study was on the structure of the high school math curriculum and how it influences both students' progress in the mathematics pipeline and also their achievement.

Two features of the high school mathematics curriculum were found to be especially influential in determining how far students get. One element targets the low end of the curriculum: more coursetaking activity at the low end of the curriculum (below the level of Algebra I) leads to students making less progress. On the other end, we found that students move farther through the curriculum in schools that offer calculus. Further, when there is less variation in the number and type of low-level courses taken, the courses students take are more equitably distributed by family social class. Our multivariate analyses indicated that in schools whose curricula include fewer courses taken below algebra and more high-end offerings (especially calculus), students progress farther in the mathematics curriculum.[16]

<u>Curriculum structure and achievement</u>. In general, we conclude that the findings of this study provide evidence that is consistent with the constrained curriculum approach laid out at the beginning of the report. When the high school mathematics curriculum is structured by limiting low-end course options, students typically move farther through the curriculum and average achievement in the school is higher. However, more variation within schools in how far the students get in the pipeline, on average, is associated with *higher* achievement, not lower.[17] Although average progress in the mathematics pipeline was unrelated to social equity in the distribution of achievement, more variability among low-level credits in that curriculum resulted in more inequality in achievement within schools by student SES.[18]

Sector, curriculum, and achievement. In this study, there were few significant effects of school sector on the outcomes. Although no-difference findings typically are not discussed in a report such as this, we highlight our non-findings regarding school sector for several reasons. Several other studies about the high school curriculum have used a school sector focus (e.g., Bryk, et al 1993; Lee & Bryk 1989). We also used sector differences as a guiding framework to structure our review of the literature. In addition, in this sample we found observed sector differences in curriculum, reported in the descriptive information in table 2.

We offer two possible explanations for the lack of sector differences here. The first focuses on our analytic models. Once curriculum structure was included in the multivariate models, in general the effects of school sector (i.e., comparisons of Catholic and NAIS schools to public schools) disappeared. Of course, academic organization (or curriculum structure) represents a major difference between private and public secondary schools, as we described at the beginning. Therefore, controlling for structural differences explained away sector differences. A second explanation focuses on our sample. Because all of the schools in the HSES sample are located in or near America's largest cities, schools in rural areas, those in and around towns and villages, and schools in mid-sized cities are not represented. It is also possible that the difference between this sample of schools and students and samples used in prior studies of this topic (that were closer to being nationally representative) accounts for differences between our findings and those of other studies with a similar focus.

Some Implications of These Findings

Composition. What kinds of students go to which types of schools, and what happens to those students in their schools, are fundamental questions embedded in school effects studies such as this one. In this study, we found strong effects for school social and academic composition. The HLM models took into account many social and academic characteristics of students, as well as the structure of the high school curriculum. However, even when these controls were included, students' progress in the mathematics course pipeline and their achievement were shown to be adversely affected when there are high proportions of low-achieving students in the school, even when students' own academic status at the beginning of high school is taken into account.

This finding is consistent with conclusions made by Barr and Dreeben (1983) and by Rutter and his colleagues (1979). Although those two studies examined learning in schools with different contexts, the authors of both studies described the detrimental effects on overall achievement when there are large proportions of low-performing students in an educational setting. The context for Barr and Dreeben's study was first-grade classrooms; Rutter et al. studied inner-city London secondary schools.

We found that social as well as academic composition is important; the social-class level of the school influences achievement, even when several academic characteristics of students and schools were taken into account. This finding touches on the issue of access. U.S. students are mapped to high schools either through residential location, by parental choice among public schools, or through parents' and students' interest, ability, and willingness to consider private schools. Residential location, by far the most common determinant of school social and academic composition, is associated with family income. Increasingly, students and their families may choose the high school they attend. Choice of school, as well as willingness to exercise choice, is also related to family background (Carnegie Foundation for the Advancement of Teaching 1992; Lee, Croninger, & Smith 1994). The issue of access involves equity between schools, whereas the focus on equity in this study was within schools. Nevertheless, our findings underscore the importance of school social composition in determining average coursetaking and average achievement, above and beyond the structure of the curriculum.

<u>Low-level mathematics courses</u>. Most studies of curriculum structure and achievement have focused on the high end of the mathematics curriculum. Our investigation of schools that offer large numbers of low-level courses—and the association of this type of curriculum with students' coursetaking and achievement—are new. We demonstrate that when schools offer many low-end courses, students don't move very far into the higher end of the curriculum. When schools offer fewer of these courses, students take fewer of them (see technical note 16). Instead, they take more advanced courses, the type of courses that much research (including this study) has shown to be associated with achievement (Lee, et al [1993] review this research). Virtually every high school, district, and state requires at least two years of mathematics to graduate, and some require more. Thus, students have to take some mathematics courses. The question is, "Which ones do they take?"

Although taking low-level mathematics courses is associated with lower achievement, the curriculum in comprehensive high schools typically contains many such courses. The rationale for offering these courses may be that high school staff feels a responsibility to respond to perceived or actual student demand. When such courses are available, however, many students choose (or are counseled into) them. Some students are highly motivated or follow advice from parents who are well aware of the long term implications of taking demanding courses. Other adolescents, however, may not be academically ambitious or prepared to dive into demanding academic courses, and some parents may not have the experience and knowledge to offer guidance in this respect. The results of this study are consistent with conclusions made by Philip Cusick, who discussed the implications of extensive student choice in high schools that offered a broad curriculum with many undemanding courses. He called this system: ...electiveness accompanied by an open, non-tracked system... There are high school students who are either very mature or who have sufficient parental guidance to help them make their choices. But for those who are neither mature nor receiving any parental guidance, such a system may further disadvantage the already disadvantaged (Cusick 1983, p.76).

We also found that high school curriculum structure influences social equity in achievement. When there is greater variation in a school's pattern of mathematics courses taken below Algebra I, there is more inequity in both coursetaking and achievement within the school. It is often socially disadvantaged students who take large numbers of low-level courses (Lee & Bryk 1988, 1989; Lee, Smith, & Croninger 1997; Oakes 1990).

These results, coupled with findings that demonstrated that schools where students took many low-end courses had lower achievement, suggest a direction for reform of the mathematics curriculum in U.S. high schools. High schools might consider the impact of offering no more than a very small number of courses below the level of Algebra I. These are, in essence, remedial courses. Taking such courses should be an unusual event, intended only as remediation to prepare students to take academic math courses.[19] Perhaps schools and districts might want to re-evaluate whether students should be able to satisfy graduation requirements with low-level courses. If these types of courses meet these requirements, students can graduate without having taken any academic courses.

Specialized vs. constrained curriculum, revisited. The findings of this study are consistent with the constrained curriculum approach in high school mathematics. However, the specialization model remains dominant in U.S. comprehensive high schools. Historically, the comprehensive public high school has been an institution that under one roof serves students with a wide range of abilities, interests, and future plans (Cusick 1983; Powell, et al 1985). The need to serve a diverse group of students in U.S. schools is as important today as it was at the beginning of this century. There are, however, several modes of meeting this goal. U.S. public high schools have traditionally approached this task by offering separate programs to diverse groups of students (Oakes 1985; Powell, et al 1985). Catholic high schools, with a similar tradition of educating socially and academic diverse students and families, historically approached the same task rather differently (Bryk, et al 1993).

This curriculum full of specialization and choice became the dominant mode of public secondary school design when young people could leave high school and move into relatively high paying jobs that required few skills learned in school. As Murnane and Levy (1996) point out, however, the workplace that young people now face looks quite different. These authors conclude that all students need solid mathematical skills to function in the workplace of the 21st century, whether or not they are planning to attend college, whether or not they are intellectually curious, and whether or not they are highly motivated to engage in academic work while they are in high school. Regardless of future plans or present inclinations, all students now need a solid base in mathematics.

Our results show that high schools where students take more mathematics courses offer fewer low-end courses. When schools offer mostly demanding academic courses, students advance further through the academic math curriculum. This pattern of student coursetaking is associated with their attaining higher achievement by the time they finish high school. In general, the results described in this report and the conclusions and implications we draw from them are consistent with several other of our published articles that focus on the general topic of curriculum structure (Lee 1993; Lee & Bryk 1988, 1989; Lee, Croninger, & Smith 1997; Lee, Smith, & Croninger 1997).

Other Conclusions From This Study

How this study differs from other school effects studies. Because school effects studies investigate how the characteristics of schools influence the students attending those schools, analysis in such studies should reflect the nature of the research questions—they should be multilevel. Because this study falls into the school effects category, we used such multilevel methods. Methodologically, the study described in this report is similar to several other recent studies on this topic that we described at the beginning. However, this research differs in other ways from those studies. The comments in this section may be most relevant for researchers considering the HSES data for their own studies. In particular, we discuss some differences between the HSES data compared to NELS:88.

To whom may we generalize? One difference is the sample. Compared to school effects studies that used NELS:88 data, the HSES data offer several advantages. One is larger within-school sample sizes. Statistical theory tells us that larger within-group samples lead to more precise estimates of the random parameters investigated in multilevel analysis (here, we estimated coursetaking and achievement, as well as relationships between both of these outcomes and student SES within each school). Another advantage is that NCES has supplied school-level design weights with the HSES data. High-school weights are not included in the NELS data files; researchers who wished to pursue this type of study had to either confine their analyses to the student level, run multilevel analyses unweighted, or make their own school weights. None of these options is satisfactory for secondary data analysts, particularly those who may not be fully familiar with the NELS school "sampling strategy."

On the other hand, researchers who use the HSES data should give considerable thought to how the sample of schools and students used in this study departs from national representativeness. The original sample of HSES schools comes only from the areas in and around America's largest cities, so schools in rural areas are excluded. Researchers also need to consider the procedure used to augment the sample of tenth graders within the HSES schools. In each high school in the HSES sample, the entire group of NELS students who were selected originally (in 1988) and were tenth graders (in 1990) was retained in the HSES within-school sample. However, augmentation samples of students in each school were drawn randomly from among the remaining tenth graders in the school. Thus, the combined sample of students within schools actually is two separate samples: one is a de facto sample (the original NELS students) and one is close to a randomly drawn sample. As these are actually two student samples, researchers cannot be sure how representative the combined sample of students in each school is of the population of 1990 tenth graders in that school. Additionally, the large amount of missing data in the HSES leaves researchers unclear about the representativeness of the operational sample even compared to the original HSES sample described in the codebook (Scott, et al 1996). These questions about sampling raise issues about the population of students and schools to whom results should be generalized.

Statistical control for ability. The structure of the HSES dataset, and how it differs from that of the "parent" NELS data files, may have influenced the findings from this study. The base year of HSES is 1990, when students were near the end of the tenth grade. Data were collected for the first time from the augmented portion of the student sample half way through high school, compared to the full NELS (for which data are available from students before they entered high school in 1988). Thus, for only part of the HSES sample are test scores available at high school entry. If researchers wish to measure achievement gain over the four years of high school, which is necessary if they wish to assess the full impact of attending high schools on students (the essence of a school effects study), then the HSES dataset as a whole will not allow this kind of investigation. Our approach to this problem was to include a proxy measure of mathematical ability, the grades students earned in math during their first year of high school. Of course, use of this proxy factors out a quarter of students' experiences in high school.

We suggested that this measure was a reasonable proxy for mathematical ability. On the other hand, our measure is clearly not as good as a score on a test of achievement that is on the same scale as the outcome measure. We recognize that this control for mathematical ability at the start of high school may offer imperfect adjustment for this important personal characteristic. In addition to tapping student ability, course grades usually reflect school grading policies, relative student performance, and non-academic behavior. The lack of objective ability measures on students just before they enter high school, particularly achievement, is a drawback of using HSES data for school effects study compared to NELS, where test scores are available on virtually all students at eighth grade.

Our conclusions here are identical to those made by Lee and Bryk (1989), who commented on their research using the High School and Beyond data:[20] "There is always the possibility, of course, that the estimated school effects may be somewhat different if we had a better measure of the initial ability of students" (1989, p.186). Although we could have used the measure of mathematics achievement at the end of tenth grade as a statistical control for ability, we suggest that by doing this we would be controlling away even more of the school effects we wish to estimate.

> Were sophomore achievement used as a proxy for differences in ability on entry into high school, the effects of school organization on the social distribution of achievement would be almost entirely adjusted away because much of these distributional differences are likely to be in place by the end of the sophomore year (Lee & Bryk 1989, p. 177).

<u>A new measure of curriculum structure</u>. The variable we used to operationalize students' progress in the mathematics pipeline represents an innovation in several respects over past efforts to measure the construct of coursetaking. First, rather than focusing only on the number of mathematics courses taken (or even the number of academic courses completed), our measure focuses on the most advanced course students have taken in high school. Thus, this measure serves as an indicator of both the quantity and the content of courses taken. Second, because we drew information about coursetaking from students' transcripts rather than from self-reports, the measure is quite reliable. Third, the school-level aggregate of this measure (and its standard deviation) represents one of several indicators (or perhaps a byproduct) of the structure of the high school mathematics curriculum. Hopefully, our efforts here represent an advancement in conceptualizing high school curriculum structure. Other researchers should consider this new indicator and perhaps apply the idea to other subjects in the curriculum.

The effects on learning are indirect. Both our findings and our conceptualization of how the structure of the high school mathematics curriculum influences students' achievement in this subject (from figure 1) suggest an alternative approach. Our findings indicate that curriculum structure influences achievement mostly indirectly, following a two-stage process. In the first step, what courses a school offers (how many of which type) determines in large part what courses students take, even after accounting for their demonstrated performance in the subject. In the second step, the number and type of courses students take determine their achievement. Research on this topic might focus more fruitfully on investigating indirect effects such as these, rather than the typical approach of estimating only direct influences on achievement. Actually, it is usually total effects that researchers what to know, represented by the combination of direct and indirect effects.

Final Comments

Our final comments are both substantive and methodological. Our results suggest that where students go to high school has implications for their success. The composition of some high schools, with large numbers of low-achieving students and large proportions of economically disadvantaged students, is associated with lower student achievement (above and beyond the disadvantage individual students experience from low SES and low achievement status at entry). The implications from the findings of this study also pertain to possible reform of the high school math curriculum, at both low and the high end. The results may also have implications for the curriculum in elementary and middle schools. Mathematics is a cumulative subject requiring mastery of lower-level concepts before more advanced topics can be undertaken. To reach a skill level in mathematics during high school that is recognized as useful after graduation, in general students should be computationally and conceptually able to take Algebra I at high school entry (i.e., in the 9th grade).

In at least three respects, this study represents an innovation compared to other recent studies of curriculum structure (some of them our own). One contribution is the new measure of curriculum structure, one that adds a new dimension to this work. Another contribution is the larger samples of students within schools compared to other studies with NELS data. Larger within-group samples allow more precise estimates of the constructs that are the focus of any study of this type. A third contribution relates to the conceptualization of the process through which curriculum structure influences achievement, a process that is to a great extent indirect as well as direct.

On the other hand, we see a few limitations to using the HSES data for investigations of this type. One is the smaller and potentially unrepresentative sample of high schools. Another is the lack of data on a substantial proportion of HSES students as they enter high school, as well as difficulties involved in estimating school effects only for the last half of high school. Clearly, researchers who are interested in pursuing investigations that focus on school effects need to consider these issues as they undertake their work and make decisions about the best data and methods to use.

Technical Notes

1. Although the words *excellence* and *effectiveness* have similar meanings in the context of this study, we use the first in reference to student outcomes and the second in reference to *school outcomes*.

2. The initial baseline sample size was 9,146 students. After data collection, however, the effective sample size dropped to 7,642 (Scott, et al 1996). We began our sample selection with this group. The excluded students had no questionnaire data.

3. We created a new flag for students with complete mathematics achievement scores (both tenth and twelfth) because we found that the original test flag (S290TPFL) includes students with incomplete mathematics test information.

4. In both the text of this report and in Appendix C (where we describe the construction of all variables used in the study), we provide somewhat more information than we would for a scholarly article about the same study (e.g., we have provided actual names of HSES variables for sampling and variables). Because these data are new and somewhat unfamiliar to researchers, even those who are familiar with NELS, we hope to make others' analyses of HSES data somewhat easier than ours has been.

5. Schools who belong to the National Association of Independent Schools are homogeneous in the sense that the schools typically are quite selective in two regards. First, the tuition at these schools are quite high (especially compared to Catholic schools), so the schools are selective in an economic sense. Second, many of these schools have academic entrance criteria, so that many NAIS schools are selective in an academic sense. The title "independent" is quite appropriate; the schools are almost entirely autonomous from external control. In other places, we have referred to NAIS schools as "elite private schools."

6. During the HLM estimation procedure, in the presence of unequal within-school sample sizes, each school's contribution is weighted proportionally to its statistical "precision." As the within-school sample size decreases, so does its precision. Consequently, such schools (with fewer than 5 sampled students) are downweighted during the estimation process. Eliminating such schools from the analysis, although not absolutely necessary, tends to improve the efficiency of the algorithm (Bryk & Raudenbush 1992).

7. Group-mean centering is a scaling alternative to grand-mean centering. In the former, the option we employed in this study, the within-school predictors are centered around their corresponding school means. This results in intercepts that can be interpreted as the adjusted mathematics progress (or mathematics achievement) for "average" students in the schools (where "average" is relative to the schools' students). In the latter, the within-school predictors are centered

around the single grand mean. This results in intercepts that can be interpreted as the adjusted mathematics progress (or math achievement) for “average” students (where “average” is defined independent of schools).

8. The purpose of using effect sizes (measured in SD units) is that they are consistent across outcomes measured in different metrics. Thus, they represent a standardized measure of the strength of a statistical relationship. Substantive interpretation of effect sizes suggests that effects over .5 SD are considered large, those between .3 and .5 SD are moderate, those between .1 and .3 SD are small, and those below .1 SD are trivial (Rosenthal & Rosnow 1984).

9. Naturally, such claims about the students in a school (e.g., all students in the school complete calculus) depend upon the randomness of the within-school sample. Strictly speaking, all students sampled from the school completed calculus. The larger within-school sample sizes available in HSES minimize the likelihood that such patterns are subject to substantial sampling error.

10. The average number of completed credits below algebra is a rather gross estimate of average coursetaking behavior in the school in large part because of the severe positive skew within the school: in many schools a large proportion of the students complete no low-level coursework in mathematics. Hence, the school average combines students with no low-level coursework and students with possibly many years of low-level coursework.

11. There is a distinction between within-category variation (captured by the SDs of the means for each of the three groups: low, middle, and high) and within-school variation (captured by the within-school SDs). The first measure of variation is an estimate, for example, of the similarity of all high-progress schools (e.g., high-progress schools as a group offer on average fewer low-level mathematics courses [mean number of courses = 2.1, see table 2], but there is substantial deviation from that mean within the category of high-progress schools [standard deviation of the means = 1.9, see table 2]). In other words, there are some high-progress schools which offer fewer low-level courses and some high-progress schools which offer more low-level courses. In addition, we consider the within-school SDs which are a measure of the variability around the school mean, or a measure of the similarity of students within the school.

12. Taking social and academic background into account in these within-school HLMs has increased the lambda reliabilities of the intercepts somewhat: .806 for the highest course taken (Model 1), .775 for mathematics achievement in Model 2A, and .852 for achievement in Model 2B, compared to .770 and .719 for the two measures as shown in table 3. The SES/outcome slopes are much less reliable: the reliability of the SES/coursetaking slope is .237, and the SES/achievement slope reliability is .260 for Model 2A and .329 for Model 2B. These reliabilities are comparable to those reported in other school-effects studies that consider slopes as outcomes.

13. The within-school HLM models shown in table 4 are rather different from OLS (ordinary least squares) regressions, in that the hierarchical structure of these models takes systematic differences between high schools into account. This is a major advantage of HLM over OLS.

14. The measure of low-level courses offered had almost no effect, whereas the measure of the number of credits in low-level courses completed was significantly related to the outcome. It is possible that the differences in effects from the two measures (which supposedly tap the same general construct) relate to the source of the information for each. Principals may not have an accurate picture of the courses actually offered in any given year (but rather may be reporting on those in the school's course catalogue). On the other hand, students can only take courses that are actually taught. Thus, our credits measure represents a more accurate accounting of what a school's mathematics curriculum actually represents.

15. We also ran a set of HLM analyses with the same two sets of curriculum structure controls shown in table 6, but where the within-school model was identical to that shown in Model 2A of table 4. As the results were very similar to those shown in table 6, we have not included them here.

16. Our multivariate HLM models include several measures of a school's curriculum structure. As indicated in Appendix C, the measure of courses offered was drawn from principals' reports, whereas the measures of courses taken were aggregated from student reports. These two measures, which tap the same construct, are highly correlated. It is likely that the collinearity between high schools' offering more courses and a large amount of coursetaking activity in those courses is measuring the same thing. Because we use the aggregate measure of student coursetaking as a proxy measure of offerings (i.e., high school curriculum structure), we draw conclusions related to schools' curricular offerings. Lee and Smith (1995), Lee, Smith, and Croninger (1997) and Lee, Croninger, and Smith (1997) follow this same procedure for measuring curriculum structure.

17. More variation within schools suggests the possibility of more students at the low end and/or the high end of the mathematics course pipeline. In general, larger within-school variation is associated with lower average pipeline progress ($r = -.36$). However, after controlling for average progress, the fact that greater variation leads to higher achievement suggests that the greater variation in this sample is most likely associated with more students at the higher end of the pipeline.

18. We have chosen to put a substantive meaning on this finding. However, it is possible that there is an artifactual explanation. The findings for social composition are similar to those reported in many studies (including our own), but our findings about the academic composition are unusual. It is possible that this context effect is due, at least in part, to our use of the aggregate of our proxy

measure of student ability—ninth grade mathematics GPA—as a measure of academic composition.

19. The typical practice for remediation in Catholic high schools is quite different from remedial courses in comprehensive public high schools (Bryk, et al 1993). If, for example, a student entered a Catholic high school without the skills to succeed in Algebra I, the student would typically be enrolled in that class as a ninth grader. However, he or she would also be enrolled in a remedial (and non-credit) class simultaneously; the student would be taking two math classes at the same time. Remediation would continue until the student was able to succeed in the regular academic mathematics course on his/her own. In these school settings, remedial courses do not serve as alternative ways to satisfying graduation requirements in any subject. Rather, their purpose is to bring students up to competence to succeed in academic courses. Obviously, this type of program assumes that, eventually, all students can succeed in an academic curriculum.

20. High School and Beyond (HS&B) is a nationally representative longitudinal study of high school students' educational progress conducted by the U.S. Department of Education. Data on base year samples of high school sophomores and seniors were collected in 1980, with the same students followed with biennial data collections. Researchers recognized a limitation in the HS&B design and data structure: there were no data available on students as they entered high school or during the early years of high school. To a great extent, this difficulty with HS&B guided the design of NELS:88. The HSES data suffer, however, from some of the same difficulties in design as HS&B.

References

Angus, D.L. & Mirel, J.E. (1995). *Rhetoric and reality: The American High school curriculum, 1945-1990*. In D. Ravitch and M. Vinovskis (Eds.), *Learning from the past: What history teaches us about school reform* (pp. 295-328). Baltimore, MD: Johns Hopkins University Press.

Barr, R. & Dreeben, R. (1983). *How schools work*. Chicago: University of Chicago Press.

Boyer, E.T. (1983). *High school: A report on secondary education in America*. New York: Harper & Row.

Bryk, A.S., Lee, V.E., & Holland, P.B. (1993). *Catholic schools and the common good*. Cambridge, MA: Harvard University Press.

Bryk, A.S. & Raudenbush, S.W. (1992). *Hierarchical linear models: Applications and data analysis methods*. Newbury Park, CA: Sage.

Bryk, A.S., Raudenbush, S.W., & Congdon, R.T. (1994). *Hierarchical linear modeling with the HLM/2L and HLM/3L programs*. Chicago, IL: Scientific Software International (SSI).

Carnegie Foundation for the Advancement of Teaching (1992). *School choice: A special report*. Princeton, NJ: Author.

Clune, W.H. & White, P.A. (1992). “Education reform in the trenches: Increased academic course taking in high schools with lower achieving Students in states with higher graduation requirements”. *Educational Evaluation and Policy Analysis*, 14(1), 2-20.

Coleman, J.S., Hoffer, T., & Kilgore, S.B. (1982). *High school achievement: Public, Catholic, and private schools compared*. New York: Basic Books.

Conant, J.B. (1959). *The American high school today*. New York: McGraw Hill.

Cremin, L.A. (1988). *American education: The metropolitan experience 1876-1980*. New York: Harper & Row.

Cusick, P.A. (1983). *The egalitarian ideal and the American high school*. New York: Longman.

Gamoran, A. (1987). “The stratification of high school learning opportunities”. *Sociology of Education*, 60, 135-155.

Goodlad, J. (1984). *A place called school*. New York: McGraw-Hill.

Hyde, J.S., Fennem, E., & Lamon, S.J. (1990). *Gender difference in mathematical performance: A meta-analysis*. Psychological Bulletin, 107, 139-155.

Ingels, S.J., Dowd, K.L., Baldridge, J.D., Stipe, J.L., Bartot, V.H, & Frankel, M.R. (1994). *National Education Longitudinal Study of 1988. Second Follow-Up: Student Component Data File User's Manual*. NCES94-374. Washington, DC: U.S. Department of Education, Office of Educational Research and Improvement.

Jones, L.V., Davenport, E.C., Bryson, A., Bekhuis, T., & Zwick, R. (1986). "Mathematics and science test scores as related to courses taken in high school and other factors". *Journal of Educational Measurement*, 23, 197-208.

Kleibard, H.M. (1986). *The struggle for the American curriculum 1893- 1958*. New York: Routledge.

Lantz, A.E. & Smith, G.P. (1981). "Factors influencing the choice of nonrequired mathematics courses". *Journal of Educational Psychology*, 73(6), 825-837.

Lee, V.E. (1985). *Investigating the relationship between social class and academic achievement in public and Catholic schools: The role of the academic organization of the school*. Cambridge, MA: Harvard University, unpublished dissertation.

Lee, V.E. (1993). "Educational choice: The stratifying effects of selecting schools and courses". *Educational Policy*, 7(2), 125-148.

Lee, V.E. & Bryk, A.S. (1988). "Curriculum tracking as mediating the Social distribution of high school achievement". *Sociology of Education*, 61, 78-94.

Lee, V.E. & Bryk, A.S. (1989). "A multilevel model of the social distribution of high school achievement". *Sociology of Education*, 62, 172-192.

Lee, V.E., Croninger, R.G., & Smith, J.B. (1997). "Course-taking, equity, and mathematics learning: Testing the constrained curriculum hypothesis in U.S. secondary schools". *Educational Evaluation and Policy Analysis*, 19(2), 99-121.

Lee, V.E., Croninger, R.G., & Smith, J.B. (1994). "Parental choice of schools and social stratification in education: The paradox of Detroit". *Educational Evaluation and Policy Analysis*, 16(4), 434-457.

Lee, V.E. & Ekstrom, R.B. (1987). "Student access to guidance counseling in high school". *American Educational Research Journal*, 24, 287-310.

Lee, V.E. & Smith, J.B. (1993). "Effects of school restructuring on the achievement and engagement of middle-grade students". *Sociology of Education*, 66(3), 164-187.

Lee, V.E. & Smith, J.B. (1995). “Effects of school restructuring and size on gains in achievement and engagement for early secondary school students”. *Sociology of Education*, 68(4), 241-270.

Lee, V.E. & Smith, J.B. (1996). “Collective responsibility for learning and its effects on gains in achievement for early secondary school students”. *American Journal of Education*, 104(1), 103-147.

Lee, V.E. & Smith, J.B. (1997). “High school size: Which works best, and why?” *Educational Evaluation and Policy Analysis*, 19(3), Fall 1997.

Lee, V.E., Smith, J.B., & Croninger, R.G. (1997). “How high school organization influences the equitable distribution of learning in mathematics and science”. *Sociology of Education*, 70(2), 128-150.

McDonnell, L.M. (1988). *Coursework policy in five states and its implications for indicator development*. Santa Monica, CA: Working paper for the Rand Corporation.

Monk, D. and Haller, E.J. (1993). “Predictors of high school academic course offerings: The role of school size”. *American Educational Research Journal*, 30, 3-21.

Murnane, R. (1975). *The impact of school resources on inner city children*. Cambridge, MA: Ballinger.

Murnane, R.J. & Levy, F.S. (1996). *Teaching the new basic skills: Principles for educating children to thrive in a changing economy*. New York: Free Press.

National Association of Secondary School Principals (1996). *Breaking ranks: Changing an American institution*. Reston, VA: Author, in partnership with the Carnegie Foundation for the Advancement of Teaching.

National Commission on Excellence in Education (1983). *A nation at risk: The imperative for educational reform*. Washington, D.C.: U.S. Government Printing Office.

Oakes, J. (1985) *Keeping track: How schools structure inequality*. New Haven, CT: Yale University Press.

Oakes, J. (1990). “Opportunities, achievement, and choice: Women and minority students in science and mathematics”. In C.B. Cazden (Ed.), *Review of Research in Education*, 16, 153-222.

Oakes, J., Gamoran, A., & Page, R. (1992). *Curriculum differentiation: Opportunities, outcomes, and meaning*. In P.W. Jackson (Ed.), *Handbook of research on curriculum* (pp. 570-608). New York: McMillan.

Powell, A.G., Farrar, E., & Cohen, D.K. (1985). *The shopping mall high school: Winners and losers in the educational marketplace*. Boston: Houghton-Mifflin.

Romberg, T.A. (1992). *Problematic features of the school mathematics curriculum*. In P.W. Jackson (Ed.), *Handbook of research on curriculum* (pp.749-788). New York: Macmillan.

Rosenthal, R. & Rosnow, R.L. (1984). *Essentials of behavioral research*. New York: McGraw Hill.

Rutter, M., Maughan, B., Mortimore, P., Ouston, J., & Smith, A. (1979). *Fifteen thousand hours*. Cambridge, MA: Harvard University Press.

Sandel, M. (Ed). (1984). *Liberalism and its critics*. New York: New York University Press.

Scott, L.A., Ingels, S.J., Pulliam, P., Sehra, S., Taylor, J.R., & Jergovic, D. (1996). *National Education Longitudinal Study of 1988. High School Effectiveness Study: Data File User's Manual*. Washington, DC: National Center for Education Statistics, U.S. Department of Education (March 1996).

Sizer, T.R. (1984). *Horace's compromise: The dilemma of the American high school*. Boston: Houghton-Mifflin.

Sizer, T.R. (1992). *Horace's school: Redesigning the American high school*. Boston: Houghton-Mifflin.

Tyack, D. (1974). *The one best system*. Cambridge, MA: Harvard University Press.

Useem, E.L. (1991). "Student selection into course sequences in mathematics: The impact of parental involvement and school policies". *Journal of Research on Adolescence* 1(3), 231-250.

Appendix A: Analysis of differences between included and excluded members of the analytic sample

Rationale

The purpose of this analysis is to examine potential differences between the students and schools included in our analytic sample and those students and schools that were excluded from the analysis through our sample selection criteria. The discussion is intended to describe (1) the direction of mean differences between the included and excluded samples, (2) the effect of the missing data on our analyses, and (3) the generalizability of our findings.

Analytic Sample

Our investigation required information about student demographics, coursetaking behaviors, math achievement, and a number of school structure characteristics. We selected students with complete questionnaire information (10th and 12th), complete mathematics test information (10th and 12th), complete transcript information (9th, 10th, 11th, and 12th), and complete demographic information (race/ethnicity, socioeconomic status, and gender). We also selected students in schools with administrative questionnaires available (10th and 12th), and schools that were public, Catholic, or private schools affiliated with the National Association of Independent Schools (NAIS). Finally, we selected only those schools with 5 or more students who satisfied the above criteria. These selections resulted in an analytic sample of 3,430 students in 184 schools.

Excluded Sample

The *HSES Data File User's Manual* (Scott, et al 1996) indicates that 9,146 students were selected for the 1990 baseline student sample (p. 33). This sample explicitly excluded students with the following characteristics: (1) part-time students; (2) students who transferred out of the school after the student roster was compiled; (3) students who were on the roster but not in tenth grade, or those who had been absent or truant for 20 consecutive days and were not expected to return to school; (4) physically or mentally disabled students who were unable to fill out the questionnaires or take tests; (5) students for whom English or Spanish was a second language and who lacked language proficiency to complete the questionnaires and tests; and finally (6) those students who were deceased (p. 34). Although 9,146 students were selected for the baseline sample, the *User's Manual* notes that five of these baseline students, three of whom filled out questionnaires, were found to have been sampled in error. These cases were included in the weighting, but were not included on the HSES data file (p. 33).

Of the 9,141 students initially selected for the baseline sample, only 7,642 students completed questionnaires. These participating students constitute the effective student sample (see the *HSES Data File User's Manual*, 1996, table 6.1.1-1). Unfortunately, not all of these tenth-grade students remained in the same school between 1990 and 1992. Unlike the NELS:88 study design, HSES did not attempt to follow students who dropped out or transferred to a different school. In addition to these losses, not all of the tenth-grade students who remained in the same school between 1990 and 1992 chose to fill out HSES survey questionnaires in 1992. Those students who left school or chose not to participate in the 1992 followback were excluded from our analytic student sample. Similarly, 247 schools were selected for the baseline school sample, but only 242 participated in the baseline questionnaires. These schools constitute the effective school sample from which we drew our sample.

The samples of 7,642 students in 242 schools provide the basis for our analysis of differences between those students and schools that were included in our analytic sample and those that were not. Since 3,430 students and 184 schools were included in our analytic sample, a maximum of 4,212 students and 58 schools should be considered as the excluded group. Because the number of cases missing information was different for different variables, we include specific excluded sample values in appendix tables A-1 and A-2.

Procedure

We first identified all participating baseline students (7,642) using the S1STAT baseline status indicator. Students who were included in our analytic sample (3,430) were coded 1, and students excluded from the sample (4,212) were coded 0. We then used t-tests to examine potential differences between the included and excluded students for all of the continuous student variables used in our study: socioeconomic status, 9th-grade mathematics grade point average, highest mathematics course completed, and 12th grade mathematics achievement. We used chi-square tests to examine potential differences between student-level categorical variables: gender and minority status. Note that all tests of student variables were based on unweighted means.

We followed a similar procedure to investigate potential differences between the 184 schools included in our analytic sample, and the remaining 58 schools that were not included in the analysis. We then compared the two groups of schools (included and excluded) on the school-level variables used in our study: average socioeconomic status, mean and SD of the 9th-grade mathematics grade point average, mean and SD of the highest level of mathematics courses completed, the average number of courses below algebra that a school offers, the mean and SD of the number of below algebra math credits taken by students, the mean and SD of 12th-grade mathematics achievement, school size, the number of students per school, the proportion of low-achieving students per school, school sector, a school's minority status, and the percent of schools offering calculus. Note that these tests use school weights.

Findings for Excluded Sample: Students

The results of the comparisons clearly indicate that the included and excluded student samples are demographically and academically different (see appendix table A-1). The excluded sample of students includes a significantly larger percentage of minorities *[t=7.01]* and is of significantly lower socioeconomic status *[t=-8.65]* compared to the students in the analytic sample. Excluded students also show significantly lower prior mathematics grades *[t=-6.71]*, and significantly lower 12th grade mathematics achievement levels *[t=-2.03]*. The highest level of mathematics completed by the excluded students is significantly lower than the highest level of mathematics completed by those students in the analytic sample *[t=-19.49]*. The findings in appendix table A-1 clearly indicate that those students who were excluded from the analytic sample are also more disadvantaged.

Findings for Excluded Sample: Schools

The differences between included and excluded schools appear less systematic than differences between included and excluded students (see appendix table A-2). In terms of school composition, the sample of excluded schools had a significantly larger percentage of minority students *[t=3.13)*, but the included and excluded samples are not significantly different in average socioeconomic status *[t= .67]*. The proportion of low-achieving students in the excluded school sample was significantly *lower* than the proportion of low-achieving students in the analytic sample *[t=-11.15]*. This is a curious finding that is discussed below in more detail.

In terms of structural characteristics, the average size of the excluded schools is significantly smaller than the average size of the schools in our analytic sample *[t=-5.19]*. The excluded schools also have significantly smaller within-school student samples *[t=-7.93]*. The analytic sample includes significantly larger proportions of Catholic *[t=-2.35]* and NAIS private schools *[t=-2.42]*. Given that we explicitly excluded non-NAIS private schools from our analysis, it is also unsurprising that the two samples show a significant difference in terms of sector *[t=11.90]*.

Appendix table A-2 indicates that included and excluded schools also show a number of key differences in the school composition and structure, and the structure of the mathematics curriculum. The most pronounced trend is that schools in our analytic sample tend to have significantly more variation in mathematics measures (prior grades *[t=-8.72]*, 12th grade achievement *[t=-5.58]*, and highest course completed *[t=-6.05]*), although average levels of these outcomes do not vary significantly between groups *[12th grade achievement, t=-1.01; highest math course completed, t=-.90]*. A key exception to this trend is that the average of prior mathematics grades in excluded schools was significantly *higher* than the average prior grades in our analytic sample *[t=3.68]*. This is consistent with the earlier finding that excluded schools had lower proportions of low-achieving students.

Although excluded schools have a significantly higher percentage of minority students *[t=3.13]*, a characteristic that tends to be associated with higher levels of poverty, the excluded sample shows no SES deficit *[t=.67]*. Moreover, these excluded schools appear to be advantaged in terms of student grades (recall that the proportion of low-achieving students is the proportion of students with mathematics grades below C) *[t=3.68]*. Despite the indication of high student grades, excluded schools are much less likely to offer calculus compared to schools in the analytic sample which have higher proportions of students with low grades *[t=-5.93]*. These seeming inconsistencies may be due, in part, to the collection of schools excluded from the analysis. The unweighted excluded sample includes 37 public schools, 2 Catholic schools, 4 NAIS schools, and 15 non-NAIS private schools. Further analysis revealed that the excluded public schools have lower SES *[t=-2.48]*, larger minority enrollments *[t=3.76]*, lower average 9th grade mathematics grades *[t=-2.10]*, and lower average 12th grade achievement *[t=-2.25]* than their public school counterparts in the analytic sample. The presence of these two subsamples within the excluded group helps to explain the high percentage of minority students and the lack of significant social class differences between included and excluded schools. Moreover, it seems that evidence of higher grades in the excluded schools could stem from several sources. The increased selectivity of non-public schools is likely to reduce the proportion of students with low mathematics grades and to increase the number of students with higher average early mathematics grades. Since non-public schools compose 69 percent of the weighted excluded sample, the influence of selectivity on mathematics grades is more pronounced in the set of excluded schools.

Summary

The purpose of this analysis is to examine whether systematic differences exist between those students and schools included in our analytic sample and those that are not. Ideally, the included and excluded samples would not differ. Such a finding would support the claim that our analytic sample was representative of the full HSES sample, and therefore generalizable to urban and suburban students and schools in the 30 largest U.S. metropolitan areas. However, we cannot make this claim. The analytic sample used for this study systematically excludes certain students.

Although significant compositional, structural, and curricular differences exist between schools that were included and excluded from the analysis, these differences are not systematic, and do not suggest that excluded schools are either more advantaged or more disadvantaged. However, further analysis of the excluded sample suggests that excluded public schools were significantly more disadvantaged in terms of composition and curricular structure compared to public schools included in the analysis. This suggests that our multivariate analyses may not provide adequate control for select school characteristics.

The HSES sample was designed to represent students and schools in the urban and suburban portions of the 30 largest U.S. metropolitan areas. The previous analysis suggests that our sample is generalizable to a slightly more affluent segment of students and schools within these areas. We recognize that sample selection always represents a balance between samples adequate for the type of analysis employed and generalizability. Because the full HSES sample itself is not representative of the U.S. high school population of students and schools, we conclude that our sample selection criteria are appropriate.

Appendix Table A-1.--Means and sample sizes for student-level variables

(Included, n = 3,430; excluded, n = 4,212)

Variable	Included students Mean	Excluded students Mean	Excluded students Variable-Specific Sample Size[1]
Percent Female	48	49	4,212
Percent Minority	30	38*	4,073
Social Class	.30	.14*	3,940
Mathematics GPA, Grade 9	2.46	2.28*	2,472
Highest Math Course Completed	5.69	4.80*	2,701
12th-Grade Mathematics Achievement	51.50	50.33*	932

* p<.05

1. Excluded sample means were calculated using excluded cases with available information.

SOURCE: U.S. Department of Education, National Center for Education Statistics, *High School Effectiveness Study (HSES:90/92).*

Appendix Table A-2.--Means and sample sizes for school-level variables

(Included, n = 184; excluded, n = 58)

Variable	Included schools Mean	Excluded schools Mean	Excluded schools Variable-Specific Sample Size[1]
A. School Composition	26	46*	56
Percent High Minority Schools	31	14*	58
Percent of Low-Achieving Students	.29	.33	57
Average SES	2.46	2.28*	2,472
B, School Structure			
Percent Catholic Schools	20	9*	58
Percent NAIS Schools	8	2*	58
Percent "Other" Private Schools	0	58*	58
School Size	1176	616*	58
Student Count Per School [2]	31	21*	58
C. Structure of Mathematics Curriculum			
Percent Offering Calculus	82	44*	42
Mean, Courses Offered Below Algebra	3.77	3.70	58
Mean, Credits Taken Below Algebra	.63	.72	42
SD, Credits Taken Below Algebra	.71	.66	42
D. Student Achievement			
Mean, Mathematics GPA, Grade 9	2.38	2.65*	42
SD, Mathematics GPA, Grade 9	.96	.69*	33
Mean, Mathematics 12 Achievement	50.77	49.24	49
SD, Mathematics 12 Achievement	12.21	9.91*	40
Mean, Highest Mathematics Course Completed	5.62	5.47	38
SD, Highest Mathematics Course Completed	1.26	.76*	31

* p<.05

1. Excluded sample means were calculated using excluded cases with available information.
2. This variable provides the mean number of students in each school in our sample. To obtain this number, we aggregated the student ID variable to the school level and created a new variable, which we called "count." The mean of this variable for each group is presented here.

SOURCE: U.S. Department of Education, National Center for Education Statistics, *High School Effectiveness Study (HSES:90/92)*.

Appendix B: A brief discussion of school- and student-level weights in the HSES data set

<u>The Need for Weights</u>

Because of the complex sampling strategies involved in the HSES data set, the development of school-weights was an especially complicated process:

> The difficulty in developing weights stemmed from the method of "selecting" the 10th-grade schools constituting the baseline sample. Tenth-grade schools were selected as a direct consequence of the fact that one or more NELS:88 first follow-up sample members attended the school in 1990. HSES schools were not selected with known probabilities from an initial completed sampling frame. Therefore, to create school weights, it was necessary to determine for each HSES school the probabilities associated with students' transition from a NELS:88 base year (1988) eighth-grade school to a particular 10th-grade school in 1990 (*HSES Data File User's Manual*, 1996, p. 35)

<u>Selecting a School-Level Weight</u>

Three distinct baseline weighting procedures (employing distinct probability models) resulted in a set of school-level weights (see the *HSES Data File User's Manual*, 1996, for a complete discussion of the weights). These three weights are not highly correlated with one another. Weight 1 (the Spencer-Foran weight) and weight 3 (the Qian-Frankel weight) are most highly correlated ($r = .5656$), whereas weights 2 (the Kaufman weight) and 3 are only modestly correlated ($r = .2855$). Weights 1 and 2 have a rather low relationship to one another ($r = .1496$).

In keeping with the low correlations between them, the weights perform in a differential fashion and "none of the weighting models provides consistently close agreement between population and sample estimates" (Appendix M, *HSES Data File User's Manual*, 1996. p. M-6). Our own preliminary exploration of the three weights in the context of simple HLM models of 12th-grade mathematics achievement was similarly nonconclusive. Although the size of coefficients changed under the four conditions (unweighted and weighted separately by each of the three school-level weights), in general the significance levels did not. The chi-square statistics testing between-school variation in outcomes increased when weighted, but the significance levels remained similar.

Neither our analyses nor those described in Appendix M of the *HSES Data File User's Manual* provided unequivocal evidence of the greater efficacy of a particular school-level weight. Consequently, the choice of a school-level weight seems to remain rather arbitrary. We decided to use the Qian-Frankel weight, in part because it is most strongly related to the other two (especially to the Spencer-Foran weight).

<u>Concerns with the Student-Level Weights</u>

Despite the indicated optimism—"Once school weights were developed, the calculation of student weights was a relatively straightforward process" (*HSES Data File User's Manual*, 1996,

p. 36)—the construction of the HSES student-level weights proved to be less than "straight-forward":

> Given the way in which the HSES student sample was selected, students within a selected HSES school can be treated as two strata: students who were members of the NELS:88 sample and those who were not. Since all of the students who were members of the NELS:88 sample and who were enrolled in a HSES school were included in the HSES student sample with certainty, the probability P_3 (the conditional probability that the 10th-grade student is in the HSES student sample, given that the student's 10th-grade school is in the HSES school sample) for these students equals 1. The students who were not members of the NELS:88 student sample were selected by systematic random sampling, which approximates simple random sampling without replacement. Therefore, P_3, for these students is equal to their within-school selection probability (*HSES Data File User's Manual*, 1996, p. 40).

While the conceptualization of the student sample as composed of two strata is straightforward enough, the assignment of $P_3 = 1$ for those HSES students who were members of the NELS:88 sample results in practical concerns for both (a) the overall student weights (used for descriptive purposes, factor analyses, preliminary OLS regression models, etc.) and (b) the within-school weight (used for HLM modeling). All but one of the student-level HSES weights (the exception being the student-level, 8-12 panel weight, S288PNWT) systematically downsize the original NELS:88 students within the HSES sample. This downsizing is not modest in magnitude, but essentially eliminates those cases from statistical analyses. Hence, the twofold strata are replaced with what amounts to a single stratum.

Roughly one third (unweighted) of the entire HSES sample is drawn from the original NELS:88 students. This is also true of our reduced study sample of 3430. These relative proportions are true, however, for the unweighted samples only. Employing the HSES weights reduces the stratum of NELS:88 students to less than 5 percent of the sample. This alteration in the relative proportions of sample membership affects the magnitude and significance of parameter estimates in multivariate models: weighted and unweighted results are often quite dissimilar, much more so than with other NELS studies (e.g., High School and Beyond, NELS:88).

In their current state, the HSES student-level weights are not effective or useful. New weights are being constructed that preserve both strata of the student sample. All analyses we present in this report involving student-level data are unweighted at the student level. This includes: (a) descriptive information on the student sample, and (b) HLM models (weighted using the school-level weight only—without the within-school student weight).

Appendix C: Details of construction of variables and weights used in the study of curriculum structure and mathematics achievement

All variables used in this study were drawn from the following HSES files: student, school, and transcript.

Variables Describing Students: Outcome Measures

12th Grade Mathematics Achievement. A continuous variable measuring IRT-estimated number right on the 12th grade mathematics test (S22XMIRR from student file) [M = 51.50, SD = 15.22]. For multivariate analysis, normalized on students to a z-score metric [M = 0, SD = 1].

Highest Level of Mathematics Course Completed. Eight-level variable constructed from NELS/HSES student transcript data (student course credits in mathematics). The scale was created by selecting the highest level of mathematics course each student completed with a passing grade during his/her four years in high school. More detail on the logic of construction, and how the variable behaves in multivariate analyses, is available from the authors. The variable will be available on new releases of NELS and HSES data from NCES [M = 5.69, SD = 1.66]. For multivariate analysis, normalized on students to a z-score metric [M = 0, SD = 1].

Level 1: No Mathematics. Student took no mathematics courses in high school.

Level 2: Non-Academic. General mathematics 1 or 2, basic mathematics 1, 2, or 3, consumer mathematics, vocational mathematics, or review.

Level 3: Low Academic. Pre-algebra, algebra I stretched over two years, informal geometry.

Level 4: Middle Academic I. Algebra I, plane geometry, solid geometry, unified mathematics 1 or 2, pure mathematics.

Level 5: Middle Academic II. Algebra II, unified mathematics 3.

Level 6: Advanced I. Algebra 3, algebra/trig, analytic geometry, trigonometry, probability, statistics, independent study.

Level 7: Advanced II. Pre-calculus, introductory analysis.

Level 8: Advanced III. Calculus, AP calculus, calculus/analytic geometry.

Variables Describing Students: Background Characteristics

Social Class (SES). Socioeconomic status (composite includes parents' education, father's occupation, family income, and several educationally-oriented household possessions [S2SES from the student file]), normalized on students to a z-score metric (M = 0, SD = 1).

Gender. Gender of student; coded 1 = female, 0 = male (recoded S1SEX from the student file). [48.2 percent are female, 51.8 percent are male]

Minority Status. Race/ethnicity of student; coded African American, Hispanic, or Native American = 1; White or Asian = 0 (recoded S1RACE from the student file). [30.3 percent are minority, 69.7 percent are non-minority]

9th Grade Mathematics Grades. A continuous variable indicating students' grades (at the end of 9th grade) in the subject of mathematics (taken from the transcript file) [M = 2.46, SD = 1.01]. For multivariate analysis, normalized on students to a z-score metric [M = 0, SD = 1].

Variables Describing Schools: Mathematics Curriculum Structure

School Mean, Highest Mathematics Course Completed. A school aggregate from student transcript data; the within-school average of the student-level measure: highest mathematics course completed. This measure represents the average highest mathematics course completed for each school [average of the school means = 5.62, standard deviation of the school means = 1.09]. For multivariate analysis, normalized on schools to a z-score metric [M = 0, SD = 1].

School SD, Highest Mathematics Course Completed. A school aggregate from student transcript data; the within-school standard deviation of the highest mathematics course completed. This measure represents the variability of students' mathematics coursetaking in each school [average of the school standard deviations = 1.26, standard deviation of the school SDs = .46]. For multivariate analysis, normalized on schools to a z-score metric [M = 0, SD = 1].

Number of Mathematics Courses Offered Below Algebra. School-reported curriculum offerings, sum of six dummy-coded course offerings indicators: S1C75R2 (General Mathematics, grade 9), S1C75S2 (General Mathematics, grades 10-12), S1C75T2 (Business Mathematics), S1C75U2 (Consumer Mathematics), S1C75V2 (Remedial Mathematics), S1C75W2 (Pre-Algebra), [M = 3.77, SD = 1.79]. For multivariate analysis, normalized on schools to standard deviation units [M = 2.20, SD = 1.00].

School Mean, Number of Mathematics Credits Completed Below Algebra. A school aggregate measure from student transcript data; the within-school average number of credits completed in the following mathematics courses [CSSC codes]: 270100 (MATHEMATICS, OTHER GENERAL), 270101 (MATHEMATICS 7), 270103 (MATHEMATICS 8), 270104 (MATHEMATICS 8, ACCEL), 270106 (MATHEMATICS 1, GENERAL), 270107 (MATHEMATICS 2, GENERAL), 270108 (SCIENCE MATHEMATICS), 270109 (MATHEMATICS IN THE ARTS), 270110 (MATHEMATICS, VOCATIONAL), 270111 (TECHNICAL MATHEMATICS), 270112 (MATHEMATICS REVIEW), 270113 (MATHEMATICS TUTORING), 270114 (CONSUMER MATHEMATICS), 270300 (APPLIED MATHEMATICS, OTHER), 270601 (BASIC MATHEMATICS 1), 270602 (BASIC MATHEMATICS 2), 270603 (BASIC MATHEMATICS 3), 270604 (BASIC MATHEMATICS 4), 270401 (PRE-ALGEBRA), 270402 (ALGEBRA 1, PART 1), 270403 (ALGEBRA 1, PART 2), 270409 (GEOMETRY, INFORMAL), [average of the school means = .63, standard deviation of the school means = .49]. This measure represents the average number of low-level mathematics courses completed for each school. For multivariate analysis, normalized on schools to standard deviation units [M = 1.26, SD = 1.00].

School SD, Number of Mathematics Credits Completed Below Algebra. School aggregate measures from student transcript data; the within-school standard deviation in the number of credits in the following mathematics courses [CSSC codes]: 270100 (MATHEMATICS, OTHER GENERAL), 270101 (MATHEMATICS 7), 270103 (MATHEMATICS 8), 270104 (MATHEMATICS 8, ACCEL), 270106 (MATHEMATICS 1, GENERAL), 270107 (MATHEMATICS 2, GENERAL), 270108 (SCIENCE MATHEMATICS), 270109 (MATHEMATICS IN THE ARTS), 270110 (MATHEMATICS, VOCATIONAL), 270111 (TECHNICAL MATHEMATICS), 270112 (MATHEMATICS REVIEW), 270113 (MATHEMATICS TUTORING), 270114 (CONSUMER MATHEMATICS), 270300 (APPLIED MATHEMATICS, OTHER), 270601 (BASIC MATHEMATICS 1), 270602 (BASIC MATHEMATICS 2), 270603 (BASIC MATHEMATICS 3), 270604 (BASIC MATHEMATICS 4), 270401 (PRE-ALGEBRA), 270402 (ALGEBRA 1, PART 1), 270403 (ALGEBRA 1, PART 2), 270409 (GEOMETRY, INFORMAL). [average of the school standard deviations = .71, standard deviation of the school SDs = .37]. This measure represents the variability of low-level mathematics coursetaking in each school. For multivariate analyses, normalized on schools to standard deviation units [M = 1.88, SD = 1.00].

Calculus Offered. In order to explore the availability and influence of calculus in the mathematics curriculum, we considered data from three sources: (1) the HSES Course Offerings File, (2) the HSES School File, and (3) the HSES Student Transcript File. Unfortunately, the Course Offerings File proved to be a problematic data source with substantial missing data. Over 30 of the schools in our analytic sample were missing course offerings data, and data from other schools seemed highly unlikely (e.g., one school claimed calculus as the only math course available, another school was coded as offering three years of low-level, general math and one year of calculus).

Data from the second and third sources resulted in two possible measures. The first variable used school responses (S1C75EE1 and S1C75FF1) to identify those schools that claimed to offer calculus. Unfortunately, 40 schools in our analytic sample were missing information about their calculus course offerings. Given the substantial amount of missing information, we decided to explore the possible use of aggregated student-level data.

We constructed the second variable by first identifying all students whose transcript information indicated that they had taken calculus (students who scored at the highest level on the math coursetaking variable, MTHQUAL8). We then aggregated these scores to the school-level in such a way that if at least one student in the school indicated that they had taken calculus, the school was identified as offering calculus. One of the advantages of this method is that it identifies whether calculus was actually taken in a school, and not simply whether a calculus course was "on the books." None of the schools in our analytic sample had missing data for this variable.

Comparisons between these two measures of the availability of calculus revealed some inconsistencies: (1) there were schools claiming to offer calculus but no one in our school sample had elected it, and (2) there were schools claiming not to offer calculus but sample members had nonetheless completed a calculus course. In the first instance, the discrepancy could simply be due to sampling, but it could also reflect a course that is offered only “on paper.” In the second instance, the discrepancy might occur if a student went elsewhere (i.e., a nearby college) for calculus instruction. Additional inquiries led us to believe that the measure based on actual course election was better suited for use in the multivariate models. Consequently, the availability of calculus is coded 1 = at least one student in the within-school sample completed calculus, and 0 = no one in the within-school sample completed calculus [82 percent of schools offer calculus, 18 percent do not].

Variables Describing Schools: Composition and Structure

School Sector. Two dummy variables (created from G10CTRL2, from school file):

Catholic, coded Catholic = 1, public and elite private schools coded 0.

NAIS, coded NAIS = 1, public and Catholic schools coded 0.

In multivariate analyses, public schools serve as the comparison group [72.1 percent are public, 19.9 percent are Catholic, 8.0 percent are private].

School Mean, SES. A school-level aggregate; the within-school average of the student SES variable described above [average of the school means = .29, standard deviation of the school means = .49]. This measure represents the average SES of each school. For multivariate analysis, normalized on schools to a z-score metric [M = 0, SD = 1].

School Size. Continuous variable indicating the number of students enrolled in each school (S1C2 from the school file) [M = 1176, SD = 748]. For multivariate analysis, normalized on schools to a z-score metric [M = 0, SD = 1].

Minority Concentration. A dummy-coded variable (a sum of the percent Native American 10th graders [S1C27A], percent Hispanic 10th graders [S1C27D], and percent Black (not Hispanic) 10th graders [S1C27E], from the school file); schools with proportions of minority students 40 percent or above coded 1, others coded 0. [26 percent of schools are high minority, 74 percent are low minority]

Proportion of Low-Achieving Students. This measure indicates the proportion of students in each school who earned below a ‘C’ in 9th grade mathematics [M = .31, SD = .18]. For multivariate analysis, normalized on schools to a z-score metric [M = 0, SD = 1].

School Mean, 12th Grade Mathematics Achievement. A school aggregate; the within-school average of 12th grade mathematics achievement [average of the school means = 50.77, standard deviation of the school means = 8.09]. This measure represents the average 12th grade mathematics achievement for each school. Used for descriptive purposes only.

School SD, 12th Grade Mathematics Achievement. A school aggregate; the within-school standard deviation of 12th grade mathematics achievement [average of the school standard deviations = 12.21, standard deviation of the school SDs = 2.47]. This measure represents the variability in 12th grade mathematics achievement for each school. Used for descriptive purposes only.

School Mean, 9th Grade Mathematics Grades. A school aggregate; the within-school average of 9th grade mathematics grades for each school [average of the school means = 2.38, standard deviation of the school means = .41]. This measure represents the average 12th grade mathematics grades for each school. For multivariate analysis, normalized on schools to a z-score metric [M = 0, SD = 1].

School SD, 9th Grade Mathematics Grades. A school aggregate; the within-school standard deviation of 9th grade mathematics grades [average of the school standard deviations = .96, standard deviation of the school SDs = .19]. For multivariate analysis, normalized on schools to a z-score metric [M = 0, SD = 1].

<u>Weight</u>

School-Level Weight. For all school-level analyses, descriptive and multivariate, we employ S1SCWT3, which is the Qian-Frankel weight [normalized to have a mean of 1 on our 184 schools].

Appendix D: A brief description of typical hierarchical linear models used in the study of curriculum structure and mathematics achievement

<u>Within-School Models</u>

A simple form of Hierarchical Linear Model (HLM) used in this study consists of two equations, a within- and a between-school model. Some of the parameters estimated in the within-school model become outcomes to be explained in between-school equations. Our within-school model investigates the mathematics achievement at the end of high school of student i in school j, Y_{ij}, as a function of a student's k social and academic background characteristics, X_{ijk}, and random error, e_{ij}. The X-variables discussed here are socioeconomic status (SES), gender, minority status, and students' grades in mathematics in the first year of high school, and the highest level of mathematics course the student has taken over the four years of high school. A typical HLM within-school equation is as follows:

$$MATHACH_{ij} = \beta_{j0} + \beta_{j1}SES_{ij} + \beta_{j2}FEMALE_{ij} + \beta_{j3}MINORITY_{ij} +$$

$$\beta_{j4}MTHGDES_{ij} + \beta_{j5}MATHCRS_{ij} + R_{ij}.$$

The β_{jk} regression coefficients are structural relations occurring within school j that indicate how achievement within each school is distributed across the measured student characteristics. In the HLM model that we investigated here, we were particularly interested in two β parameters:

β_{j0} = the average 12th-grade math achievement score for students in school j (adjusted for academic and social background), and

β_{j1} = the relationship between SES and achievement among students in school j, which we refer to as the SES/achievement slope.

In this model we initially estimated all distributional effects (the β parameters) in our HLM analyses. However, we were not interested in modeling the additional parameters as functions of the school organization or curricular structure. The limited sample size (and resulting degrees of freedom) within schools constrains our ability to estimate random parameters, but it does not limit the number of fixed variables that may be included as statistical controls. Consequently, between-school variability in the other within-school controls (gender, minority status, 9th-grade grades, and coursetaking) is typically constrained to 0 (i.e., they do not vary randomly between schools). Thus, a final within-school model might be:

$$\beta_{ij} = \beta_{j0} + \beta_{j1}SES_{ij} + \beta_{2}FEMALE + . . . + \beta_{5}MATHCRS_{ij} + e_{ij}.$$

Between-School Models

In the second set of equations, we model the random-effect β parameters, adjusted for student characteristics, as functions of school-level organizational and structural characteristics (W-variables). We estimate a single between-school model for each outcome, estimating the effects of contextual features on the two outcomes (β_0 and β_1). A typical between-school model is as follows:

$$\beta_{kj} = \gamma_{k0} + \gamma_{k1}W_{1j} + \gamma_{k2}W_{2j} + ... + \gamma_{kp}W_{pj} + U_{kj}.$$

The parameters of interest here are the effects associated with aspects of the school's curriculum structure (W variables), represented by the γ_{pk} (gamma) coefficients. In this instance, we might be interested in modeling between-school differences in adjusted math achievement as a function of two curriculum structure (W) variables: the average number of low-level math courses taken (LOWCRDTS) and whether the school offers calculus (CALCULUS). Although this model is considerably simplified from the full HLM models in this paper, a typical HLM between-school model might be:

$$\text{AVMTHACH } (\beta_{j0}) = \gamma_{00} + \gamma_{10}\text{LOWCRDTS}_j + \gamma_{20}\text{CALCULUS}_j + U_{j0}.$$

In this model, we interpret the gamma coefficients as school effects on average achievement as having following meaning:

γ_{00} = grand mean for adjusted 12-grade mathematics achievement;

γ_{10} = the effect of the average low-level courses taken in each school on average mathematics achievement;

γ_{20} = the effect of calculus availability in each school on average math achievement.

Similarly, we could model β_1, the SES/achievement slope—a direct measure of the social distribution of achievement in a school—as a function of factors describing school curriculum structure.

$$\text{SES SLOPE } (\beta_{j1}) = \gamma_{01} + \gamma_{11}\text{LOWCRDTS}_j + \gamma_{21}\text{CALCULUS}_j + U_{j1}.$$

Gamma coefficients, which quantify school effects on this measure of social equity within schools, have the following interpretation:

γ_{01} = grand mean for the relationship between SES and achievement (typically this is a positive relationship);

γ_{11} = the effect of the average low-level courses taken in each school on the SES/achievement slope (a positive effect increases inequity; a negative effect means more social equity); and

γ_{21} = the effect of calculus availability in each school on the SES/achievement slope (similar meaning for positive and negative effects).

Because error terms in HLM within-school (e_{ij}) and between-school models (U_{kj}) are complex, conventional linear model techniques (e.g., analysis of variance or ordinary squares regression) are inadequate for the estimation procedure. However, developments in statistical theory and computation, available through the HLM software, make such estimation possible with maximum likelihood procedures (see Bryk and Raudenbush, 1992, for details). Briefly, the total variance in each outcome is partitioned into two components: parameter and error variance. Only effects on the parameter variance are estimated in HLM. This is an important distinction, as it is only variability in the structural parameters, $Var(\beta_{jk})$, which can be explained by factors describing curriculum structure. Efforts to estimate school effects with general linear model methods have typically resulted in their being systematically underestimated for this reason.

Listing of NCES Working Papers to Date

Please contact Ruth R. Harris at (202) 219-1831 (ruth_harris@ed.gov)
if you are interested in any of the following papers

Number	Title	Contact
94-01 (July)	Schools and Staffing Survey (SASS) Papers Presented at Meetings of the American Statistical Association	Dan Kasprzyk
94-02 (July)	Generalized Variance Estimate for Schools and Staffing Survey (SASS)	Dan Kasprzyk
94-03 (July)	1991 Schools and Staffing Survey (SASS) Reinterview Response Variance Report	Dan Kasprzyk
94-04 (July)	The Accuracy of Teachers' Self-reports on their Postsecondary Education: Teacher Transcript Study, Schools and Staffing Survey	Dan Kasprzyk
94-05 (July)	Cost-of-Education Differentials Across the States	William Fowler
94-06 (July)	Six Papers on Teachers from the 1990-91 Schools and Staffing Survey and Other Related Surveys	Dan Kasprzyk
94-07 (Nov.)	Data Comparability and Public Policy: New Interest in Public Library Data Papers Presented at Meetings of the American Statistical Association	Carrol Kindel
95-01 (Jan.)	Schools and Staffing Survey: 1994 Papers Presented at the 1994 Meeting of the American Statistical Association	Dan Kasprzyk
95-02 (Jan.)	QED Estimates of the 1990-91 Schools and Staffing Survey: Deriving and Comparing QED School Estimates with CCD Estimates	Dan Kasprzyk
95-03 (Jan.)	Schools and Staffing Survey: 1990-91 SASS Cross-Questionnaire Analysis	Dan Kasprzyk
95-04 (Jan.)	National Education Longitudinal Study of 1988: Second Follow-up Questionnaire Content Areas and Research Issues	Jeffrey Owings
95-05 (Jan.)	National Education Longitudinal Study of 1988: Conducting Trend Analyses of NLS-72, HS&B, and NELS:88 Seniors	Jeffrey Owings

Listing of NCES Working Papers to Date--Continued

Number	Title	Contact
95-06 (Jan.)	National Education Longitudinal Study of 1988: Conducting Cross-Cohort Comparisons Using HS&B, NAEP, and NELS:88 Academic Transcript Data	Jeffrey Owings
95-07 (Jan.)	National Education Longitudinal Study of 1988: Conducting Trend Analyses HS&B and NELS:88 Sophomore Cohort Dropouts	Jeffrey Owings
95-08 (Feb.)	CCD Adjustment to the 1990-91 SASS: A Comparison of Estimates	Dan Kasprzyk
95-09 (Feb.)	The Results of the 1993 Teacher List Validation Study (TLVS)	Dan Kasprzyk
95-10 (Feb.)	The Results of the 1991-92 Teacher Follow-up Survey (TFS) Reinterview and Extensive Reconciliation	Dan Kasprzyk
95-11 (Mar.)	Measuring Instruction, Curriculum Content, and Instructional Resources: The Status of Recent Work	Sharon Bobbitt & John Ralph
95-12 (Mar.)	Rural Education Data User's Guide	Samuel Peng
95-13 (Mar.)	Assessing Students with Disabilities and Limited English Proficiency	James Houser
95-14 (Mar.)	Empirical Evaluation of Social, Psychological, & Educational Construct Variables Used in NCES Surveys	Samuel Peng
95-15 (Apr.)	Classroom Instructional Processes: A Review of Existing Measurement Approaches and Their Applicability for the Teacher Follow-up Survey	Sharon Bobbitt
95-16 (Apr.)	Intersurvey Consistency in NCES Private School Surveys	Steven Kaufman
95-17 (May)	Estimates of Expenditures for Private K-12 Schools	Stephen Broughman
95-18 (Nov.)	An Agenda for Research on Teachers and Schools: Revisiting NCES' Schools and Staffing Survey	Dan Kasprzyk
96-01 (Jan.)	Methodological Issues in the Study of Teachers' Careers: Critical Features of a Truly Longitudinal Study	Dan Kasprzyk

Number	Title	Contact
96-02 (Feb.)	Schools and Staffing Survey (SASS): 1995 Selected papers presented at the 1995 Meeting of the American Statistical Association	Dan Kasprzyk
96-03 (Feb.)	National Education Longitudinal Study of 1988 (NELS:88) Research Framework and Issues	Jeffrey Owings
96-04 (Feb.)	Census Mapping Project/School District Data Book	Tai Phan
96-05 (Feb.)	Cognitive Research on the Teacher Listing Form for the Schools and Staffing Survey	Dan Kasprzyk
96-06 (Mar.)	The Schools and Staffing Survey (SASS) for 1998-99: Design Recommendations to Inform Broad Education Policy	Dan Kasprzyk
96-07 (Mar.)	Should SASS Measure Instructional Processes and Teacher Effectiveness?	Dan Kasprzyk
96-08 (Apr.)	How Accurate are Teacher Judgments of Students' Academic Performance?	Jerry West
96-09 (Apr.)	Making Data Relevant for Policy Discussions: Redesigning the School Administrator Questionnaire for the 1998-99 SASS	Dan Kasprzyk
96-10 (Apr.)	1998-99 Schools and Staffing Survey: Issues Related to Survey Depth	Dan Kasprzyk
96-11 (June)	Towards an Organizational Database on America's Schools: A Proposal for the Future of SASS, with comments on School Reform, Governance, and Finance	Dan Kasprzyk
96-12 (June)	Predictors of Retention, Transfer, and Attrition of Special and General Education Teachers: Data from the 1989 Teacher Followup Survey	Dan Kasprzyk
96-13 (June)	Estimation of Response Bias in the NHES:95 Adult Education Survey	Steven Kaufman
96-14 (June)	The 1995 National Household Education Survey: Reinterview Results for the Adult Education Component	Steven Kaufman

Listing of NCES Working Papers to Date--Continued

Number	Title	Contact
96-15 (June)	Nested Structures: District-Level Data in the Schools and Staffing Survey	Dan Kasprzyk
96-16 (June)	Strategies for Collecting Finance Data from Private Schools	Stephen Broughman
96-17 (July)	National Postsecondary Student Aid Study: 1996 Field Test Methodology Report	Andrew G. Malizio
96-18 (Aug.)	Assessment of Social Competence, Adaptive Behaviors, and Approaches to Learning with Young Children	Jerry West
96-19 (Oct.)	Assessment and Analysis of School-Level Expenditures	William Fowler
96-20 (Oct.)	1991 National Household Education Survey (NHES:91) Questionnaires: Screener, Early Childhood Education, and Adult Education	Kathryn Chandler
96-21 (Oct.)	1993 National Household Education Survey (NHES:93) Questionnaires: Screener, School Readiness, and School Safety and Discipline	Kathryn Chandler
96-22 (Oct.)	1995 National Household Education Survey (NHES:95) Questionnaires: Screener, Early Childhood Program Participation, and Adult Education	Kathryn Chandler
96-23 (Oct.)	Linking Student Data to SASS: Why, When, How	Dan Kasprzyk
96-24 (Oct.)	National Assessments of Teacher Quality	Dan Kasprzyk
96-25 (Oct.)	Measures of Inservice Professional Development: Suggested Items for the 1998-1999 Schools and Staffing Survey	Dan Kasprzyk
96-26 (Nov.)	Improving the Coverage of Private Elementary-Secondary Schools	Steven Kaufman
96-27 (Nov.)	Intersurvey Consistency in NCES Private School Surveys for 1993-94	Steven Kaufman

Listing of NCES Working Papers to Date--Continued

Number	Title	Contact
96-28 (Nov.)	Student Learning, Teaching Quality, and Professional Development: Theoretical Linkages, Current Measurement, and Recommendations for Future Data Collection	Mary Rollefson
96-29 (Nov.)	Undercoverage Bias in Estimates of Characteristics of Adults and 0- to 2-Year-Olds in the 1995 National Household Education Survey (NHES:95)	Kathryn Chandler
96-30 (Dec.)	Comparison of Estimates from the 1995 National Household Education Survey (NHES:95)	Kathryn Chandler
97-01 (Feb.)	Selected Papers on Education Surveys: Papers Presented at the 1996 Meeting of the American Statistical Association	Dan Kasprzyk
97-02 (Feb.)	Telephone Coverage Bias and Recorded Interviews in the 1993 National Household Education Survey (NHES:93)	Kathryn Chandler
97-03 (Feb.)	1991 and 1995 National Household Education Survey Questionnaires: NHES:91 Screener, NHES:91 Adult Education, NHES:95 Basic Screener, and NHES:95 Adult Education	Kathryn Chandler
97-04 (Feb.)	Design, Data Collection, Monitoring, Interview Administration Time, and Data Editing in the 1993 National Household Education Survey (NHES:93)	Kathryn Chandler
97-05 (Feb.)	Unit and Item Response, Weighting, and Imputation Procedures in the 1993 National Household Education Survey (NHES:93)	Kathryn Chandler
97-06 (Feb.)	Unit and Item Response, Weighting, and Imputation Procedures in the 1995 National Household Education Survey (NHES:95)	Kathryn Chandler
97-07 (Mar.)	The Determinants of Per-Pupil Expenditures in Private Elementary and Secondary Schools: An Exploratory Analysis	Stephen Broughman
97-08 (Mar.)	Design, Data Collection, Interview Timing, and Data Editing in the 1995 National Household Education Survey	Kathryn Chandler

Listing of NCES Working Papers to Date--Continued

Number	Title	Contact
97-09 (Apr.)	Status of Data on Crime and Violence in Schools: Final Report	Lee Hoffman
97-10 (Apr.)	Report of Cognitive Research on the Public and Private School Teacher Questionnaires for the Schools and Staffing Survey 1993-94 School Year	Dan Kasprzyk
97-11 (Apr.)	International Comparisons of Inservice Professional Development	Dan Kasprzyk
97-12 (Apr.)	Measuring School Reform: Recommendations for Future SASS Data Collection	Mary Rollefson
97-13 (Apr.)	Improving Data Quality in NCES: Database-to-Report Process	Susan Ahmed
97-14 (Apr.)	Optimal Choice of Periodicities for the Schools and Staffing Survey: Modeling and Analysis	Steven Kaufman
97-15 (May)	Customer Service Survey: Common Core of Data Coordinators	Lee Hoffman
97-16 (May)	International Education Expenditure Comparability Study: Final Report, Volume I	Shelley Burns
97-17 (May)	International Education Expenditure Comparability Study: Final Report, Volume II, Quantitative Analysis of Expenditure Comparability	Shelley Burns
97-18 (June)	Improving the Mail Return Rates of SASS Surveys: A Review of the Literature	Steven Kaufman
97-19 (June)	National Household Education Survey of 1995: Adult Education Course Coding Manual	Peter Stowe
97-20 (June)	National Household Education Survey of 1995: Adult Education Course Code Merge Files User's Guide	Peter Stowe
97-21 (June)	Statistics for Policymakers or Everything You Wanted to Know About Statistics But Thought You Could Never Understand	Susan Ahmed
97-22 (July)	Collection of Private School Finance Data: Development of a Questionnaire	Stephen Broughman

Listing of NCES Working Papers to Date--Continued

Number	Title	Contact
97-23 (July)	Further Cognitive Research on the Schools and Staffing Survey (SASS) Teacher Listing Form	Dan Kasprzyk
97-24 (Aug.)	Formulating a Design for the ECLS: A Review of Longitudinal Studies	Jerry West
97-25 (Aug.)	1996 National Household Education Survey (NHES:96) Questionnaires: Screener/Household and Library, Parent and Family Involvement in Education and Civic Involvement, Youth Civic Involvement, and Adult Civic Involvement	Kathryn Chandler
97-26 (Oct.)	Strategies for Improving Accuracy of Postsecondary Faculty Lists	Linda Zimbler
97-27 (Oct.)	Pilot Test of IPEDS Finance Survey	Peter Stowe
97-28 (Oct.)	Comparison of Estimates in the 1996 National Household Education Survey	Kathryn Chandler
97-29 (Oct.)	Can State Assessment Data be Used to Reduce State NAEP Sample Sizes?	Steven Gorman
97-30 (Oct.)	ACT's NAEP Redesign Project: Assessment Design is the Key to Useful and Stable Assessment Results	Steven Gorman
97-31 (Oct.)	NAEP Reconfigured: An Integrated Redesign of the National Assessment of Educational Progress	Steven Gorman
97-32 (Oct.)	Innovative Solutions to Intractable Large Scale Assessment (Problem 2: Background Questionnaires)	Steven Gorman
97-33 (Oct.)	Adult Literacy: An International Perspective	Marilyn Binkley
97-34 (Oct.)	Comparison of Estimates from the 1993 National Household Education Survey	Kathryn Chandler
97-35 (Oct.)	Design, Data Collection, Interview Administration Time, and Data Editing in the 1996 National Household Education Survey	Kathryn Chandler
97-36 (Oct.)	Measuring the Quality of Program Environments in Head Start and Other Early Childhood Programs: A Review and Recommendations for Future Research	Jerry West

Listing of NCES Working Papers to Date--Continued

Number	Title	Contact
97-37 (Nov.)	Optimal Rating Procedures and Methodology for NAEP Open-ended Items	Steven Gorman
97-38 (Nov.)	Reinterview Results for the Parent and Youth Components of the 1996 National Household Education Survey	Kathryn Chandler
97-39 (Nov.)	Undercoverage Bias in Estimates of Characteristics of Households and Adults in the 1996 National Household Education Survey	Kathryn Chandler
97-40 (Nov.)	Unit and Item Response Rates, Weighting, and Imputation Procedures in the 1996 National Household Education Survey	Kathryn Chandler
97-41 (Dec.)	Selected Papers on the Schools and Staffing Survey: Papers Presented at the 1997 Meeting of the American Statistical Association	Steve Kaufman
97-42 (Jan. 1998)	Improving the Measurement of Staffing Resources at the School Level: The Development of Recommendations for NCES for the Schools and Staffing Survey (SASS)	Mary Rollefson
97-43 (Dec.)	Measuring Inflation in Public School Costs	William J. Fowler, Jr.
97-44 (Dec.)	Development of a SASS 1993-94 School-Level Student Achievement Subfile: Using State Assessments and State NAEP, Feasibility Study	Michael Ross
98-01 (Jan.)	Collection of Public School Expenditure Data: Development of a Questionnaire	Stephen Broughman
98-02 (Jan.)	Response Variance in the 1993-94 Schools and Staffing Survey: A Reinterview Report	Steven Kaufman
98-03 (Feb.)	Adult Education in the 1990s: A Report on the 1991 National Household Education Survey	Peter Stowe
98-04 (Feb.)	Geographic Variations in Public Schools' Costs	William J. Fowler, Jr.

Listing of NCES Working Papers to Date--Continued

Number	Title	Contact
98-05 (Mar.)	SASS Documentation: 1993-94 SASS Student Sampling Problems; Solutions for Determining the Numerators for the SASS Private School (3B) Second-Stage Factors	Steven Kaufman
98-06 (May)	National Education Longitudinal Study of 1988 (NELS:88) Base Year through Second Follow-Up: Final Methodology Report	Ralph Lee
98-07 (May)	Decennial Census School District Project Planning Report	Tai Phan
98-08 (July)	The Redesign of the Schools and Staffing Survey for 1999-2000: A Position Paper	Dan Kasprzyk
98-09 (Aug.)	High School Curriculum Structure: Effects on Coursetaking and Achievement in Mathematics for High School Graduates—An Examination of Data from the National Education Longitudinal Study of 1988	Jeffrey Owings