Career and Technical Education and Academic Progress at the End of High School: Evidence from the Education Longitudinal Study of 2002

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Robert Bozick
Ben Dalton
RTI International

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EXECUTIVE SUMMARY

This report examines the efficacy of career and technical education (CTE) for assessing students in learning mathematics and preventing students from dropping out of high school. CTE is a wide field of educational practice that includes occupational training and career preparation offered in formats ranging from individual courses to comprehensive programs at the secondary and postsecondary levels. Recent changes in the policy environment emphasizing academic progress for CTE students have made proper evaluation of the influence of CTE on outcomes such as mathematics learning and dropping out of high school increasingly important.

This report uses data from the Education Longitudinal Study of 2002 (ELS:2002), a recently completed national-level study of high school students. ELS:2002 began with a nationally representative sample of 10th-graders in public and private schools in the United States in 2002. Sample members were surveyed again in the spring of 2004, when most were high school seniors. In the spring of 2005, transcripts were collected from these students' high schools. Using these data with methods that correct for common challenges in determining the influence of CTE, this report contrasts the effects of academic courses and occupational courses on mathematics learning and dropping out of high school for students in the ELS:2002 sample who attended public schools. Key student subgroups defined by the No Child Left Behind Act are examined closely, and attention is paid to alternative ways of defining and analyzing occupational coursetaking.

Research Questions

Reflecting the current policy environment's focus on academic progress for students who enroll in CTE courses, this report addresses two questions:

- Are credits earned in CTE courses associated with achievement growth in mathematics in the last 2 years of high school?
- Are credits earned in CTE courses associated with the decision to drop out in the last 2 years of high school?
- Is the relationship between credits earned in CTE courses and academic progress contingent upon the context of the school?

Answers to these questions are fundamental in providing guidance to policy makers and educational practitioners about how best to structure the curriculum to maximize the outcomes of CTE and other students.

The Relationship Between Career and Technical Education and Mathematics Achievement

The report examines mathematics achievement in high school using an overall test score and five scores measuring the likelihood of mastery over specific and progressive benchmarks. The analysis employs fixed-effects regression analysis to control for possible student self-selection biases. Fixed-effects regression models analyze within-person variation over time. Therefore, time-invariant characteristics—such as sex, race/ethnicity, and innate ability (whether measured or unmeasured in the study)—are effectively held constant in these analyses. Additional controls are included to eliminate the potentially confounding effects of characteristics that vary over time. Key findings include the following:

- ***The total number of occupational credits earned during the last 2 years of high school has no relationship to the number of correct answers on the mathematics assessment. However, when occupational courses comprise a larger percentage of the total number of courses taken, students answer fewer questions correctly on the mathematics assessment.*** In terms of overall proficiency on the mathematics assessment, there are no differences between students who take a small set of occupational courses alongside their academic courses and students who take only academic courses. When students take more occupational courses relative to academic courses during the last 2 years of high school, they answer slightly fewer questions correctly on the mathematics assessment. Though this relationship remains statistically significant after controlling for a range of factors, its magnitude, however, is substantively small. For example, those who earned at least 7.5 credits in academic courses and 3 credits in occupational courses (comprising almost a third of the analytic sample) are predicted to answer less than one fewer questions correctly on an 81-item test than those who earned 10.5 credits in academic courses and 0 credits in occupational courses (comprising less than a seventh of the analytic sample).

- ***Occupational credits earned in the last 2 years of high school do not limit gains in basic and intermediate mathematics skills and concepts. However, taking relatively more occupational courses and fewer academic courses during the last 2 years of high school limits the acquisition of advanced mathematics skills and concepts.*** The development of skills such as simple arithmetic operations, operations with decimals and fractions, and basic problem-solving is not compromised by enrollment in occupational courses. The development of advanced mathematics skills such as solving multistep word problems is impeded when occupational courses comprise a larger share of students' course schedules. Though this relationship, again, remains statistically significant after controlling for a range of factors, its magnitude is substantively small. For example, those who earned at least 8.5 credits in academic courses and 2 credits in occupational courses were less than a half percent less likely to be proficient at level 4, one of the most advanced skill levels, than those who earned 10.5 credits in academic courses and 0 credits in occupational courses.

- ***Occupational courses have similar effects on gains in mathematics achievement for both economically disadvantaged and affluent students as well as nonnative English speakers and native English speakers. Black and Asian students benefit more from occupational courses than do White students.*** Occupational courses improve the development of basic and intermediate skills more for Black students than for White students, while the development of intermediate and advanced skills is fostered more for Asian students than for White students.

- ***In general, science/technology/engineering/mathematics (STEM) courses in the CTE curriculum neither enhance nor compromise overall math achievement.*** Improving learning in mathematics is largely a function of traditional academic mathematics courses.

- ***Attendance at a full-time CTE school or a school located in a rural area is not related to mathematics gains.*** In addition, effects of occupational coursetaking on math achievement gains do not vary by full-time CTE school attendance. However, compared with students attending suburban schools, occupational coursetaking is less harmful to math achievement gains for rural school attendees.

The Relationship Between Career and Technical Education and Dropping Out

The relationship between dropping out of high school from the sophomore year on and CTE coursetaking was examined through a set of event history regression models predicting the odds of dropping out. A variety of student covariates and some school-level characteristics were held constant in the analyses. Courses were calibrated to match the timing of first dropping out by putting both on the basis of semester calendars. Key findings from this analysis are summarized below:

- ***Semester-by-semester dropout rates are generally low (2 percent or less)***. The data cover dropping out during the last 2 years of high school. In this period, dropout rates increased each semester from the spring of students' sophomore year to the typical end of high school for most students (2 years later). Then in the fall semester following the "on-time" graduation date for the cohort, over half of the remaining students dropped out.

- ***High school dropouts typically accumulate fewer academic credits than enrolled students over the same period of time; however, dropouts and enrolled students earn similar numbers of occupational credits***. When comparing dropouts to enrolled students in any given semester, differences in the number of earned academic credits between students who drop out and students who remain enrolled are striking. However, no differences in occupational credits earned were observed.

- ***Controlling for socioeconomic and academic differences among students as well as semester timing, accumulated credits in occupational courses are unrelated to the likelihood of dropping out***. However, students who have accumulated relatively more credits in academic courses have a reduced likelihood of dropping out. On average, each additional academic credit earned lowers the odds of dropping out by 19 percent.

- ***The cumulative number of occupational credits relative to academic credits is positively associated with dropping out. However, this relationship is driven by low academic coursetaking among students enrolled in occupational courses.*** When occupational credits earned are considered relative to academic credits earned, a greater tilt toward occupational credits is related to a greater likelihood of dropping out. This relationship holds even when student socioeconomic and academic characteristics associated with dropping out are held constant. However, students with high numbers of academic credits and high occupational credits are no more or less likely to drop out than other students, indicating that accumulating a low number of academic credits drives the relationship between relative occupational coursetaking and dropping out. This is seen when considering the effects of specific coursetaking patterns: students with no occupational courses and students with an occupational course concentration (29 percent of all course credits being occupational courses) have nearly the same probability of dropping out, at 8 and 9 percent respectively.

- ***Attendance at a full-time CTE school or a school located in an urban area is not related to dropping out.*** Additionally, effects of occupational coursetaking on dropping out do not consistently vary by full-time CTE school attendance or rural school attendance (in which one might also expect a more positive influence of occupational courses on high school persistence).

In interpreting the findings, readers should keep in mind that ELS:2002 is an observational data set based on a longitudinal study. As such, students were not randomly assigned to schools, classrooms, or course sequences, limiting the ability to establish a causal link between CTE courses and academic progress. Furthermore, this study follows students from the end of their sophomore year forward, therefore precluding an assessment of CTE and academic progress during the first 2 years of high school.

In conclusion, this study shows that CTE is limited as a policy designed to improve learning gains in mathematics and prevent dropping out of high school. Students make the largest gains in mathematics and are least likely to drop out when they enroll in academic courses. Any detected negative effect of CTE—for example, on dropping out of high school—is substantively negligible and mostly driven by preexisting differences between students who follow a CTE-focused curriculum and students who follow an academic-focused curriculum.

INTRODUCTION

The last 2 years of high school mark the culmination of approximately 13 years of structured schooling experiences. During this time, students are making decisions about their futures—continuing education in a college, university, or certificate/license program; entering the paid work force; or in many cases, a combination of the two. At the same time, students are taking courses that cover the most advanced skills and topics and many are taking courses designed to teach skills and concepts needed for specific occupations. As shown in a host of past research, these curricular experiences are vital in preparing youth for the challenges of postsecondary life, be it further education, employment, or both. The present study examines the effect of coursetaking—specifically occupationally focused courses that comprise the career and technical education curriculum—in learning gains in mathematics and dropping out of high school across different schooling contexts. First, the policy environment within which this study is embedded is briefly described. Next, the findings from previous research are summarized and the limitations from these analyses are discussed. Following this, the data and methods used are described and the findings presented. The report concludes with a summary of the main findings.

Policy Context

High school graduates increasingly require strong quantitative and technological knowledge to succeed in a highly competitive and global economy. Countries that hope to compete in advanced and technologically intensive fields must adequately train and equip students for sustained occupational success after formal schooling ends. At a national level, this requires ensuring academic learning for all students alongside special efforts to maintain the progress of disadvantaged students who are often at the highest risk of dropping out. Career and technical education (CTE), aims to assist students in meeting challenging academic and technical standards to meet the challenges of a diverse and changing workplace.

Many contemporary ideas and concerns regarding the role of schooling in preparing youth for the labor force stem from a series of high-profile reports published in the early and mid-1980s (Castellano, Stringfield, and Stone 2002). The report inaugurating this series was the National Commission on Excellence in Education's *A Nation at Risk* (1983), which challenged the presumption that American schools could keep pace with a changing national and global economy and which argued for increased academic course requirements for high school graduation as a remedy (Johnston and Packer 1987). Subsequent reports continued to emphasize academic requirements while extending critiques to weak workplace skills that students were obtaining through their education (Murnane and Levy 1996; Secretary's Commission on Achieving Necessary Skills 1991).

Since 1990, a series of federal legislative changes have been enacted in response to these reports and other concerns about American competitiveness in an increasingly global and technologically sophisticated world (U.S. Department of Education 2004). The first of these was the Carl D. Perkins Vocational and Applied Technology Act, commonly referred to as Perkins II, which was passed into law in 1990. Perkins II required vocational programs receiving federal funding to place greater emphasis on both work experience and on academic coursetaking. Technical preparation programs (or "tech prep" as it is commonly called), envisioned as a structured high school to community college educational sequence, were a major component (Parnell 1985; Prager 1994). The last 2 years of high school would focus on academics in applied and work-related settings, followed by enrollment in a 2-year postsecondary school, which would develop the in-depth technical knowledge required for full-time work. Under this model, postsecondary courses would be aligned with high school courses. The academic emphasis in high school was also to be realized by integrating academic material with vocational applications.

Perkins II was followed in 1994 by the School to Work Opportunities Act (STWOA). STWOA continued to emphasize academic goals but placed additional emphasis on providing high school students with relevant work-related experience, career awareness activities, and other work-based involvement. Career days, internships, school-based enterprises, and job shadowing were some of the work-related activities STWOA stressed.

Four years later, in 1998, Perkins III reauthorized the Perkins II legislation with a number of modifications. Perkins III sought flexibility so that it could accommodate the overall educational reform goals that states were trying to implement. The Act funded programs that, among other things, involved parents and employers in vocational education efforts, developed the use of advanced technology in training, and provided professional development for teachers and administrators. Continuing emphasis was placed on ensuring that vocational students were receiving rigorous academic instruction while at the same time providing students with work-related experiences. Perkins III operated longer without reauthorization than Perkins II (see below), but the policies it supported were a combination of developed programs supported by prior Acts, such as tech prep, alongside new forms of career and technical education (which, in 1998, began replacing the term "vocational") such as career pathways and career academies (U.S. Department of Education 2004).[1]

The next reauthorization took place 8 years later. This legislation, referred to as Perkins IV, continues to fund many of the same activities that Perkins III and earlier CTE legislation funded. However, following the passage of the No Child Left Behind (NCLB) Act, which codified the movement toward test-based accountability, Perkins IV emphasizes even further the academic outcomes and the reporting and measurement of CTE outcomes. For example, Perkins IV frequently uses terms such as "rigorous and challenging" to describe the academic and technical instruction that it is designed to support; other language explicitly addresses the mathematics and science content that is often necessary for successful technical training. It also requires states to provide indicators of their postsecondary CTE programs. Additional differences include greater emphasis on training and professional development for teachers and administrators and a reemphasis on the linkage between postsecondary and secondary curriculum such as requiring states to consult with postsecondary practitioners in developing CTE programs.

[1] The terms "vocational" and "CTE" are both used throughout this report. However, the term CTE is used to describe research, including the findings from the present study, conducted on youth attending school "post-Perkins III" and the term vocational is used to describe research conducted on youth attending school "pre-Perkins III."

Thus, the current federal climate, governed by Perkins IV, supports a wide variety of both recurring and novel CTE programs and activities within the broader policy context of accountability (principally state reporting of CTE outcomes) and the backdrop of concerns about preparation for high-skill jobs in a globally competitive economy. Despite some changes, increasing academic achievement for CTE students remains a policy goal, improving technical proficiency, fostering persistence, and promoting high school completion.

The present study examines the experiences of students attending high school following the passage of Perkins III. Thus, the findings in this report do not necessarily reflect the recent reforms that comprise Perkins IV. While CTE encompasses a range of programs and activities, this report focuses only on the courses taken by students, with special attention paid to the efficacy of an integrated academic and occupational curriculum. As such, this study serves as a gauge of the relationship between CTE and academic progress at the start of the 21st century and, consequently, may inform curricular programming decisions currently being implemented under Perkins IV. The current study builds on a body of research that has assessed the role of occupationally focused education during the evolving policy environment described thus far. This body of research provides the backdrop to the current analytical design and is described in the next two sections.

Research Questions

In an attempt to better evaluate the relationship between CTE and academic performance, this study will address the following three questions:

1. Are credits earned in CTE courses associated with achievement growth in mathematics over the last 2 years of high school?
2. Are credits earned in CTE courses associated with the decision to drop out of high school?
3. Is the relationship between CTE coursework and academic progress contingent upon the context of the school?

Answers to these questions are fundamental in providing guidance to policy makers and educational practitioners about how best to structure the curriculum to maximize the experiences of CTE students. Previous research addressing these questions is described below.

The Relationship Between Career and Technical Education and Learning

The efficacy of an educational policy is most often evaluated by its ability to increase student achievement, typically in core academic subjects such as mathematics, science, and English. To this end, standardized achievement tests are often employed as "objective yardsticks," permitting straightforward comparisons among different groups of students experiencing different "educational treatments." Although convenient in their application and interpretation, these tests may not fully measure the skills and concepts intended by a particular policy. As a consequence, the use of standardized achievement test scores to evaluate policy effectiveness may, in some cases, present only a partial view.

The provision of CTE is a prime example of a policy whose goals and objectives cannot be completely evaluated with conventional standardized tests.[2] For example, the Perkins IV legislation specified both academic *and* occupationally based indicators of CTE success (at the secondary level):

> Student attainment of challenging academic content standards and student academic achievement standards…and student attainment of career and technical skill proficiencies, including student achievement on technical assessments, that are aligned with industry recognized standards, if available and appropriate (Public Law 109–270, 109th Congress).

While academic achievement is a key component of any educational policy initiative, equally important for the provision of CTE is the development of problem-solving skills, work attitudes, general employability skills, technical skills, and occupation-specific skills. Consequently, studies that rely on standardized achievement tests that solely measure academic competencies fail to capture the breadth of learning that takes place in CTE classrooms.

Given the incongruence between the overall aim of CTE and the relatively narrow scope of standardized achievement tests that cover academic content, it is not surprising that the empirical evidence linking occupational coursetaking and student achievement has so far yielded mixed results. Since CTE courses are not designed to cover the most advanced academic content—instead focusing on work-based applications and processes—comparisons between academically focused students with occupationally focused students sometimes show the latter to be at a disadvantage (Kaufman, Bradby, and Teitelbaum 2000; Plank 2001). For example, using transcript information and test scores from the National Education Longitudinal Study of 1988 (NELS:88), Plank (2001) compared the achievement gains of students who concentrated only in academic courses, students who concentrated only in vocational courses, and students who concentrated in both (referred to as dual concentrators). After adjusting for background characteristics and baseline achievement, vocational concentrators and dual concentrators had lower test score gains in mathematics, science, reading, and history when compared with academic concentrators. Similar findings emerged from an examination of the relationship between work-based internships and standardized test scores among students in high schools that participated in the High Schools That Work network of the Southern Regional Education Board (Kaufman, Bradby, and Teitelbaum 2000): involvement in these programs was associated with lower levels of achievement in science, mathematics, and reading.

Not all analyses, however, find negative effects of participation in CTE. For example, Agodini (2001) also analyzed NELS:88 and found that while academic concentrators have the greatest learning gains, dual concentrators learn more in mathematics than their peers who followed a strict vocational curriculum. Further, he found that among those who had no intention to go to college, dual concentrators had greater gains in reading than did those who concentrated

[2] In this review, the acronym CTE refers to the range of activities and programs that connect work-based learning with academic skills (e.g., occupational courses, career and tech prep school attendance, and cooperative internships). Emphasis is given to studies that examine coursetaking, the focus of the present study.

solely in vocational courses *or* academic courses—suggesting that for certain groups of students, an integrated curriculum may be the most effective means of instruction. Using a continuous indicator that identifies the number of Carnegie units[3] earned in occupational courses rather than the categorical indicators of occupational program participation used by Plank (2001) and Agodini (2001), Rasinksi and Pedlow (1998) found that the volume of CTE coursetaking had no relationship—either positive or negative—with learning gains in mathematics, science, or reading.

Similar analyses using other indicators of academic success also yield mixed findings. Using grade point average (GPA) as an indication of learning alleviates some of the problems with the standardized achievement tests—namely, their narrow focus on one subject. GPA measures performance specific to the set of courses in which the student is enrolled. However, much like the aforementioned analyses that rely on standardized achievement scores, those that use GPA as a gauge of the effectiveness of CTE also find mixed results: some find that CTE program participation is associated with lower grades (Frasier and Starkman 2004; Lynch 2000), some find that CTE program participation is associated with improved grades (Elliott, Hanser, and Gilroy 2001; Maxwell 1999; Stern, Dayton, Paik, and Weisberg 1989; Stern, Dayton, Paik, Weisberg, and Evans, 1988), and others find mixed results (Stone and Aliaga 2003). Despite its flexibility in capturing performance across courses, because of differences in course content, performance criteria, and grading policies, GPA remains a relatively crude indicator for making comparisons among students exposed to different curricula.

Taken together, the research to date paints a fuzzy portrait. As stated in the legislation, CTE is intended to improve both the academic and occupational skills of high school students. On the academic end, analyses that use either standardized academic achievement scores or GPA find mixed results. On the occupational end, there is not a developed body of research using occupational skill assessments to draw upon. To our knowledge, assessments that gauge occupation-specific content have not been used to evaluate the learning that takes place within a CTE curriculum at a national level. As a consequence, the efficacy of CTE, as it is defined by the Perkins legislation, lacks consistent empirical evidence for a thorough evaluation.

The Relationship Between Career and Technical Education and Dropping Out of High School

In addition to improving the acquisition of academic and occupational skills, the Perkins legislation also lists high school completion as one of the goals of CTE, under the premise that practical learning will maintain the interest of those students who otherwise might be "turned off" by a class schedule filled with only academic courses. This idea is rooted in the developmental perspective on high school dropouts, which depicts a process of disengagement that spans the elementary and middle school years, culminating in withdrawing from high school without a diploma. As early as first grade, youth receive signals about their abilities to succeed—through grades, test scores, and daily feedback from their teachers and their peers (Alexander, Entwisle, and Kabbani 2001). This process congeals as students progress through school (e.g., low achievers are often held back a grade and placed into remedial courses and/or low-ability

[3] A Carnegie unit is equal to a course taken every day, one period per day, for a full school year.

groups during elementary school and middle school) (Alexander, Entwisle, and Dauber 1994; Oakes 1985). The signals they receive about their ability and their potential to succeed threaten their sense of self and reduce their motivation to work hard (Alexander, Entwisle, and Kabbani 2001).

Once these students arrive at high school, many of them have already been discouraged from academics and many turn to employment as a means to acquire career-relevant training, to make money, and to acquire status not granted in the classroom. Research on high school dropouts links these cumulative experiences with decisions to leave school: those with a history of academic difficulty are likely to find little reward in high school and drop out. Therefore, one goal of CTE is to provide a curriculum that meets the needs of these students by linking work-based concepts and skills with academic ones, by demonstrating the application of these skills in both a classroom and a work environment, and by providing practical knowledge that best fits the students' career goals. Accordingly, it is the hope of policy makers and educational practitioners that CTE will make schooling relevant to those students who might otherwise leave.

A handful of studies support the contention that the provision of an occupationally focused curriculum reduces the odds of dropping out (Arum 1998; Cellini 2006; Elliott, Hanser, and Gilroy 2002; Kemple and Snipes 2000; Maxwell and Rubin 2002). In his analysis of the High School and Beyond (HS&B) Longitudinal Study, Arum (1998) found that increased business and trade-technical coursework was associated with higher odds of school completion, particularly in states that allocated sufficient funds for vocational education. Similarly, Cellini's (2006) analysis of the 1997 National Longitudinal Survey of Youth (NLSY97) shows that participation in tech prep programs is positively related with completing high school. A handful of local CTE program evaluations finds like results (Elliott, Hanser, and Gilroy 2002; Kemple and Snipes 2000; Maxwell and Rubin 2002).

These positive outcomes are not replicated across all studies. For example, Ainsworth and Roscigno's (2005) examination of NELS:88 finds that credits in "blue collar" vocational courses are associated with an increased risk of dropping out of high school. Crain et al. (1999) analyzed the outcomes of approximately 9,000 urban students assigned to either a career magnet program or a regular curriculum in a comprehensive high school.[4] Those in career magnet programs had higher dropout rates than those in comprehensive schools. Other studies find that CTE is *unrelated* to dropping out of high school (Agodini and Deke 2004; Kemple and Scott-Clayton 2004; Neumark and Joyce 2001; Pittman 1991), and some find mixed results (Catterall and Stern 1986). These studies suggest that in some, but not all cases, CTE could have the unintended consequence of pushing students out of school.

Two recent studies by Plank and his colleagues (2001; Plank, DeLuca, and Estacion 2008) suggest that the relationship between CTE coursework and dropping out is curvilinear, which may account for the null and/or mixed findings seen in previous analyses that assume linearity. Using NELS:88 data, Plank (2001) used the cumulative ratio of CTE credits to academic credits as a means to capture the time-varying intensity of CTE participation over the

[4] The application process was structured so that half of students would be admitted by lottery and half admitted based on selective criteria (although the selective half was split between low-socioeconomic status (SES) and high-SES students).

course of high school. He found that students, particularly those who are low achievers, have the lowest odds of dropping out when they earn three Carnegie units of CTE for every four academic units. However, their odds of dropping out *increase* if they earn greater or fewer CTE credits per academic course. Plank, DeLuca, and Estacion (2008) replicated this analysis with the NLSY97 and found the same pattern, albeit weaker. In this replication, students have the lowest odds of dropping out when they earned one CTE unit for every two academic units. Taken together, these two studies suggest that CTE may be most effective in preventing dropping out when it is balanced with academic coursework.

In sum, empirical studies that examine the relationship between CTE and dropping out, much like the research on learning gains described in the previous section, find mixed results. CTE's effect on dropping out—either positive or negative—may not be not monotonic, but rather contingent on funding for these initiatives, the types of courses or programs considered, and the mix of courses taken. The present study focuses specifically on the mix of courses taken by replicating the general approach used by Plank (2001) and Plank, DeLuca, and Estacion (2008). In doing so, this study aims to illuminate how different combinations of academic and CTE courses may work to sustain enrollment.

School Context and the Efficacy of CTE

Like most educational policies designed at the national level, the Perkins legislation faces the challenge of meeting the needs of a diverse student population who attend a variety of schools (i.e., comprehensive high schools, career-focused high schools, etc.) across different locales (i.e., urban, suburban, and rural). Since CTE is typically designed to facilitate the school-to-work transition, the organization of a school's curriculum usually aligns with the skills and training needed in the local labor market which can either emphasize or lessen the importance of academic skills. For example, a CTE program structured for work in the local automotive plant that uses a range of computerized procedures and advanced technology will likely require greater skills in math and science than a CTE program nested in a rural area where more industry-specific skills are important for success in careers such as agriculture or forestry. Moreover, the labor market *incentive* to learn advanced math skills and concepts is likely higher for the student living near the high-tech automotive plant than for the student living near a beef farm or a log mill.

In addition to the locale in which the school is found, the school itself may be structured in a way that facilitates or impedes the academic progress of students who specialize in CTE. Most students in the United States attend comprehensive high schools, which are designed to meet the needs of all students. In these environments, CTE is one of a number of options available to students. With competition for resources and students, along with the stigma that has previously accompanied enrollment in a career-oriented curriculum, CTE programs in comprehensive high schools may have difficulty integrating both academic and occupationally-relevant knowledge. CTE schools (i.e., schools that focus almost entirely on job skills and training) on the other hand, can better focus on the needs of career-focused students and their teachers without the distraction and/or competition of other departments and programs. Further, CTE students may feel more academically motivated and less socially isolated in an environment designed specifically to meet their needs.

Recent research suggests that the context of schooling may be an important consideration in assessing the ability of CTE programs to meet the goals of the Perkins legislation. For example, Levesque, Lauen, Teitelbaum, Alt, and Librera (2000) find that urban and suburban schools (as compared with rural schools) and schools with career academies[5] (as compared with schools without career academies) have stronger infrastructures in place to support CTE, such as block scheduling, career majors, school-based enterprises, and co-op/tech-prep programs. Additionally, when compared with their counterparts in rural schools and schools without career academies, urban, suburban, and schools with career academies are more likely to have an integrated academic and vocational curriculum and to have teachers attending conferences on how to integrate academic and vocational skills and concepts in the classroom. Given these differences, the present study explores whether the relationship between CTE coursetaking and academic progress is contingent on school context, with the hypothesis that students in rural schools and students attending comprehensive high schools will benefit less from CTE than their peers attending urban or suburban schools and CTE schools.

Limitations of Past Research and Contribution of the Current Study

As described earlier, the evidence on the efficacy of CTE for academic outcomes is mixed. A number of methodological limitations to previous studies may have precluded firm conclusions on the effectiveness of CTE in enhancing learning and preventing dropping out of high school. These methodological limitations include selection bias, measurement problems regarding the structure and timing of coursetaking, misalignment between the concepts covered by achievement exams and the CTE curriculum, the use of data that predate recent reforms in occupational education, and a lack of attention to the role of school context. Each are described in turn.

Selection Bias. Selection bias refers to systematic error resulting from differential, nonrandom access (or "selection") to the study population (in this case, CTE courses), therefore biasing the results. The best way to safeguard against selection bias within educational research is to conduct an experiment where students are randomly assigned to a control group or to an experimental group. We do not know of any randomized study of CTE coursetaking and only one that examines a single CTE course (Stone, Alfeld, Pearson, Lewis, and Jensen 2008). Instead, most studies rely on observational data to identify students who follow different curricula and then compare their outcomes. A large volume of literature within the sociology and economics of education shows that students are not randomly placed into different courses and/or programmatic tracks (Lucas 1999; Oakes 1985). Students with limited socioeconomic and academic resources are more likely to take CTE courses than are students with more plentiful socioeconomic and academic resources. For example, recent analyses of the Education Longitudinal Study of 2002 (ELS:2002), the data used in this study, show that 21 percent of the senior class of 2003–04 who focused on occupational courses came from the lowest

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[5] The findings from Levesque et al. (2000) are based on the NLSY:97, which mistakenly excluded vocational schools, therefore precluding direct comparisons between comprehensive high schools and vocational schools. Although both comprehensive schools and CTE schools can have career academies, the estimates for schools with career academies provided here serve as a proxy for schools that have well-developed CTE programs (which is presumably the case for career-focused schools).

socioeconomic status (SES) families, compared with only 8 percent who came from the highest SES families (Planty, Bozick, and Ingels 2006). Additionally, seniors who concentrated in academic courses were twice as likely as those who concentrated in CTE courses to spend more than 4 hours per week on extracurricular activities, suggesting that occupational concentrators may be more disengaged from school and their classmates than their academically focused peers (Planty, Bozick, and Ingels 2006). Accordingly, most studies employ regression strategies to adjust for observed socioeconomic and academic characteristics when establishing the relationship between CTE and academic outcomes. Despite these statistical adjustments, however, it is possible that *unobserved characteristics* could influence both participation in CTE programs and the outcome. These unmeasured characteristics, unaccounted for in traditional regression models, may make it appear that CTE coursetaking influences math learning and dropout behavior. That is to say, CTE coursetaking may be endogenous with dropping out and poor performance. Therefore, the estimated effects of coursetaking using observational data are potentially misleading and, consequently, the causal effect of CTE is unclear.

Measurement of Coursetaking. Studies that assess learning gains have typically operationalized coursetaking two ways: (1) with a categorical measure indicating different curricular pathways such as academic concentrator, vocational concentrator, dual concentrator, and general curriculum (Agodini 2001; Kaufman, Bradby, and Teitelbaum 2000; Plank 2001); or (2) with a continuous measure indicating the number of Carnegie units earned (Rasinski and Pedlow 1998). Both are limited in that they do not capture the relative balance of CTE courses with academic courses, which is particularly important in the Perkins IV policy environment. The first approach classifies students based on meeting certain criteria (e.g., students who earn three credits in vocational courses are classified as vocational concentrators). This approach, however, does not consider the total number of credits that students earn. For example, consider two students: student A earned 17 academic credits and 5 vocational credits while student B earned 21 academic credits and 3 vocational credits. Both would be considered vocational concentrators, although the second student has both a higher total and a higher percentage of academic credits than the first student. The second approach is more flexible in that it measures the total number of credits that students earn. However, it is not sensitive to the constraints of students' course schedules. Since course schedules are largely a zero-sum arrangement, an additional course in an occupational subject usually means one fewer course in an academic subject. These tradeoffs are not captured when simply summing total credits earned. Consequently, the findings from past research that rely on these approaches are less able to gauge the relative balance of vocational and academic courses that students take—a key part of assessing curricular influences.

Timing of Coursetaking. The timing of coursetaking is a particularly thorny issue when establishing the relationship between CTE and dropping out of high school. By design, a negative relationship exists between coursetaking and dropping out: the longer students remain in school, the more courses they take. Additionally, the bulk of CTE coursetaking, especially courses that are geared toward specific labor market preparation, takes place in the last 2 years of high school, after a large portion of students who are disengaged from academic coursetaking have already dropped out.[6] Without accurately locating the timing of coursetaking in relation to

[6] A study of North Carolina public school students finds that 58.5 percent of dropouts leave school during the first 2

enrollment across all 4 years of high school and without explicitly considering the underlying monotonic relationship between coursetaking and high school persistence, studies risk misidentifying the magnitude and direction of the relationship.

Incongruence Between the CTE Curriculum and the Assessments. Most studies use academic achievement scores to measure the learning gains associated with different coursetaking patterns. However, these tests are not designed to measure many skills and concepts that are typically taught in a CTE curriculum. As a result, these assessments may understate the cognitive gains that accrue to students who follow an occupationally focused curriculum.

Old Data. Most national academic achievement data used to analyze these issues followed students before recent reforms (Perkins II and III, 1990 and 1998) in occupational education had been fully implemented. Therefore, it is not clear how CTE, as it is administered in the current policy environment, affects students.

School Context. As described earlier, schools in urban or suburban area and schools with a CTE focus are best poised to meet the goals of the Perkins legislation. However, none of the studies reviewed for this project explicitly consider the role that school context might play in enhancing or attenuating the relationship between CTE and academic progress. From a policy standpoint, if there are large differences across school contexts, it would likely be more effective to allocate funds to schools that lack the infrastructure to support successful CTE programs. To date, this line of inquiry has not been explored using national-level data.

The present study will contribute to the research base on CTE by addressing these six limitations where possible. First, this study will use fixed-effects models to assess the effect of CTE on achievement gains. Fixed-effects models eliminate the potential confounding effect of unobserved time-invariant characteristics, providing stronger causal evidence than the regression-based covariate adjustment methods used in past research with observational data. Detailed information on this method is provided in appendix A. Second, this study will use multiple measures of coursetaking, including those that capture the relative mix of CTE and academic courses, to evaluate the effectiveness of CTE. Third, the analysis of dropping out will employ event history models to capture the process of dropping out as it evolves over the course of high school. This approach will help minimize the timing problems associated with previous CTE dropout studies. Fourth, the analysis of learning will use proficiency probability scores, which provide information on the range of skills and concepts learned in mathematics. While these measures were not designed specifically with CTE curricula in mind, they provide more information on the range of skills and concepts learned than aggregate subject scores used in most research. Fifth, this project explores the experiences of a recent cohort of high school students who attended high school following the passage of the 1998 Perkins legislation (Perkins III). Finally, this project explicitly considers school locale (rural, urban, and suburban schools) and school type (comprehensive schools, CTE schools) as possibly conditioning the relationship between CTE coursework and academic progress.

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years of high school (Stearns and Glennie 2006).

Data

This analysis uses data from ELS:2002, which was designed to monitor the academic and developmental experiences of students as they proceed through high school and into young adulthood. This nationally representative study of approximately 17,590 students[7] who were 10th-graders in 2002 was sponsored by the National Center for Education Statistics (NCES).[8] Since the base-year (BY) interview in 2002, sample members have participated in two follow-up surveys: the first follow-up (F1) took place in the spring of 2004 when most were high school seniors and the second (F2) took place in 2006 when most were 2 years out of high school. Additionally, transcripts were collected from all participating sample members. This study uses data from the BY survey, the F1 survey, and the transcript study. These components are briefly described in turn.[9] Although the sample includes students in both public and private high schools, all analyses in this report are based on public school students for whom the CTE legislation is most applicable.

Base-Year Survey. ELS:2002 used a two-stage sampling procedure. In the first stage, a sample of 750 high schools, both public and private, were selected with probabilities proportional to their size. In the second stage, approximately 30 students were randomly sampled from each school on the condition that they were in the 10th grade in the spring term of the 2001–02 school year. Of the 17,590 eligible students, 15,360 completed a survey about their school and home experiences (for an 87 percent weighted response rate, based on eligible students). Of the 15,360 who completed the survey, 14,540 completed cognitive assessments in mathematics and reading (for a 95 percent weighted response rate, based on survey participants). Their parents, teachers, principals, and librarians were surveyed as well.

First Follow-Up Survey. In the spring of 2004, 14,710 of the originally selected sample members were reinterviewed (for a 95 percent weighted response rate). Some of the sample members were still in their BY school while others had transferred to a new school or were not in school because they graduated early, dropped out, or were home schooled. Similar to the BY design, the F1 included a student questionnaire and cognitive test in mathematics. High school seniors in the BY schools were typically surveyed and tested in group sessions at their schools. Seniors who had transferred to another school, dropped out, graduated, or entered a home schooling situation were usually interviewed via telephone. Only students who remained in their BY schools were administered the mathematics assessment. Results from a bias analysis comparing students who remained in the BY schools and those who had transferred to a new school, or were not in school because they graduated early, dropped out, or were home schooled are shown in appendix A. Test scores were imputed for transfer students.

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7 The sample sizes are approximate because restricted-use data are used. In accordance with NCES standards, exact sample sizes from restricted-use data files cannot be published unless the data are perturbed in some way. The perturbation approach taken here was to round the exact sample sizes of cells to 10s.

8 The study design, data collection, and data processing were undertaken by RTI International under contract to NCES.

9 For further details on the design and structure of ELS:2002, see appendix A of this report or Ingels et al. (2004, 2005).

Transcript Study Design. Starting in the winter of 2004–05, almost 1 year after most sample members had graduated from high school, transcripts were requested for all sample members who participated in at least one of the first two student interviews (BY or F1). The sample included 16,370 students, of whom transcripts were obtained for 14,290 students, for a weighted response rate of 91 percent.

Subject Area Classification

Courses in the transcript study are classified using the Classification of Secondary School Courses (CSSC) codes, a six-digit numerical code assigned to each course originally developed for the transcript component of the High School and Beyond (HS&B) longitudinal study. Since the collection of transcripts for HS&B, many changes have occurred in the high school curriculum, most notably the expansion of computer/technology-based courses and advanced courses, such as Advanced Placement (AP) and International Baccalaureate (IB) courses. To accommodate these changes, the National Assessment of Vocational Education worked to develop the Secondary School Taxonomy (SST) as a means to reclassify subject areas using the CSSC codes in 1987. This taxonomy was expanded and updated in 1994 and 1998.

At its highest (most aggregated) level, the SST divides high school coursework into four distinct curricula: academic, career and technical education (CTE), enrichment/other,[10] and special education. The academic curriculum contains six subject areas: mathematics, science, English, social studies, fine arts, and non-English language. The CTE curriculum contains three subject areas: family and consumer sciences education (FCSE), general labor market preparation (GLMP), and occupational education. FCSE courses prepare students for family and consumer roles outside the paid labor market. GLMP courses teach general employment skills that are not specific to one occupational area, such as keyboarding/typing, basic computer literacy, and general work experience courses. Occupational courses are designed to prepare students for work in a specific occupational field or related program in college. These courses are organized around 10 occupational fields or clusters:

1. Agriculture and Natural Resources
2. Science, Technology, Engineering, and Mathematics (STEM)
3. Architecture and Construction
4. Business
5. Computer and Information Sciences
6. Health Sciences
7. Manufacturing, Repair, and Transportation
8. Communications and Design
9. Personal Services and Culinary Arts
10. Public Services

[10] Enrichment/other includes general skills; health, physical, and recreational education; religion and theology; and military science.

The courses that comprise these subject areas are listed in appendix B. Since FCSE and GLMP courses are not linked to specific occupational and/or postsecondary pathways, this analysis focuses on the occupational component of CTE. Without an explicit connection to occupational programs of studies encouraged in the recent CTE legislation (and future life pathways more broadly), FCSE and GLMP courses are less central in understanding the linkages between structured occupational training and academics. Further, these courses by and large do not impart skills and concepts typically measured on a standardized mathematics achievement test.[11] In 2006, MPR Associates and NCES reclassified and reorganized courses within the CTE curriculum. The present analysis uses this revised taxonomy. It should be noted that subject areas in the SST are mutually exclusive. Therefore, a course that is classified as an academic course cannot be classified as a CTE course (or vice versa). Similarly, a course classified as academic mathematics cannot be classified as a STEM course (or vice versa). A full list of courses and their associated subject areas are provided in appendix B.

Table 1 shows the cumulative average number of CTE credits earned and the cumulative percentage classified as an occupational concentrator for the modal 4 years of school (i.e., 2000–01 is approximately the 9th grade, 2001–02 is approximately the 10th grade, etc.) for the graduating class of 2003–04 who attended public schools and had complete transcript information (N = 8,300). Sample members are classified as occupational concentrators if they earned at least two Carnegie units in one of the fields or clusters listed earlier. By the end of their first year in high school (2000–01), sample members had earned on average a little more than a third of a credit in CTE and less than 1 percent were classified as occupational concentrators. By the time they left high school (2003–04), sample members had earned on average 2.29 credits in CTE and 32.8 percent were classified as occupational concentrators.[12]

Table 1. Cumulative occupational coursetaking patterns by school year

	2000–01 school year	2001–02 school year	2002–03 school year	2003–04 school year
Mean total occupational credits earned per student	0.35 (0.02)	0.84 (.03)	1.56 (0.04)	2.45 (0.06)
Percent classified as occupational concentrators	0.72 (0.16)	8.43 (0.65)	22.14 (0.89)	35.79 (0.98)

N = 8,300

NOTE: Standard errors are in parentheses. Sample members are classified as occupational concentrators if they had earned three Carnegie units in occupational courses.

Exhibit reads: By the 2003–04 school year, students in the sample earned an average of 2.45 occupational credits and 18 percent of students in the sample were classified as occupational concentrators.

[11] In additional analyses not shown, we found that the inclusion or exclusion of FCSE and GLMP courses did not affect the findings presented in this report.

[12] Since this estimate is based on a select group of respondents that meet certain analytic criteria, these estimates can only be generalized to the population who meet the same criteria. Therefore, caution should be exercised when making comparisons with other published estimates.

Key Policy Subgroups

In accord with the No Child Left Behind legislation, states are required to track the progress of four specific subgroups, herein referred to as NCLB subgroups: economically disadvantaged students, racial and ethnic minorities, students with disabilities, and students with limited English proficiency. Since the performance of these groups is directly tied to the goals of this major policy reform, this analysis will explore whether CTE has differential effects for three of the four NCLB subgroups. Students with disabilities are not examined because of reporting inconsistencies and small sample sizes in the ELS:2002 data. Operational definitions of the other three are described below.

Economic disadvantage is defined by the student's family income (as reported by the parent) from all sources in 2001. In that year, poverty was defined as annual income less than $18,104 for a family of four. Because of the categorization of the income measure in ELS:2002, it is not possible to use that exact threshold. Instead, the closest income threshold, $20,000, is used. In this analysis, a binary variable will be used to indicate economic disadvantage: students whose families earned $20,000 or less per year are coded "1"; students who families earned more than $20,000 per year are coded "0."

Race-ethnicity is measured by a series of binary variables that indicate membership into one of six groups: American Indian/Alaska Native, Asian/Pacific Islander, Black or African American, Hispanic, White, and more than one race. To assess the differential effects for racial-ethnic minorities, all groups will be compared with Whites.

The only direct measures of limited English proficiency in ELS:2002 are teacher reported. Because the teacher reports were sometimes conflicting and/or missing, this analysis instead uses a binary variable reported by the student indicating whether he or she is a nonnative English speaker. This variable is coded "1" if English is not the student's native language and "0" if the student is a native English speaker. It should be noted that many students whose first language was other than English are fully proficient in English, especially if they have remained enrolled in high school.

II. THE RELATIONSHIP BETWEEN CAREER AND TECHNICAL EDUCATION AND MATHEMATICS ACHIEVEMENT

This section analyzes Educational Longitudinal Study of 2002 (ELS:2002) to answer the first research question: 1. Is career and technical education (CTE) coursework associated with achievement growth in mathematics over the last 2 years of high school?

Sample Selection

The analysis is based on all sample members who were in-school sophomores in 2001–02, participated in both the base-year (BY) and first follow-up (F1) interviews, completed the mathematics assessment in the BY and F1 interviews, and have complete transcript information for all 4 years of high school.[13] Of the 14,710 students who participated in both the BY and F1 interviews, 13,330 participated in the BY mathematics assessment, of whom 9,920 participated in the F1 mathematics assessment.[14] Only students who remained in their BY schools were administered the F1 mathematics assessment. Scores were imputed for students who transferred to a new school or were still enrolled in their BY school but were unable to participate during the in-school test administration. However, because mathematics achievement is the key variable in this analysis, these cases with imputed test scores were excluded to prevent any error in estimating learning gains. Lastly, 330 cases were excluded because they had no transcript information and 129 cases were excluded because they lacked evidence of both a mathematics course and complete transcript information for both the 2002–03 and 2003–04 years.[15] Of the remaining 9,460 cases, 2,300 attended a Catholic or other private school. These were excluded from the analysis. The final analytic sample includes 7,160 public school students who participated in both the BY and F1 interviews. A bias analysis comparing the composition of the analytic sample used in this analysis (N = 7,160) with the full spring 2002 sophomore cohort (N = 16,170) is presented in appendix A. The analytic sample used here has fewer economically disadvantaged students, fewer racial-ethnic minorities, and fewer low-achieving students than the full sophomore cohort. Readers should keep this caveat in mind as they interpret the findings presented in this section.

[13] The analysis includes students who had been held back a grade on the condition that they had complete coursetaking information covering the four "on-time" academic years associated with the 2002 sophomore cohort.
[14] Scores were missing for sample members in the F1 interview because they had dropped out, transferred schools, or started homeschooling. RTI only tested students who were enrolled in their BY school in the spring of 2004. By only including students who remained in their BY schools during both test administrations, the results from this analysis will not directly generalize to students who transfer in and out of school(s). For this analysis, examining students who were continuously exposed to only one curriculum and school environment, however, provides a clearer portrait of the relationship between coursework and learning.
[15] Complete transcript information is defined in this analysis as having a transcript showing enrollment in any four courses in both the 2002–03 and 2003–04 school years.

Independent Variables

The analysis uses two sets of time-varying independent variables. The first set includes three measures of academic and occupational coursetaking: (1) the number of Carnegie units earned in academic courses, (2) the number of Carnegie units earned in occupational courses, and (3) the percentage of Carnegie units earned that are classified as occupational.[16] Throughout this report, we use the phrase "courses taken" and "credits earned" interchangeably. Note, however, that in both cases we are referring to Carnegie units earned. Courses taken that did not lead to credit are not counted in the analyses. The first two measure the total number of courses earned and analytically provide estimates of the effect of an additional course in each subject area. Because, however, students' coursetaking choices are largely constrained by the number of periods available for study in the school day, their schedules are essentially a zero-sum arrangement. In other words, an additional course in an occupational subject often means one fewer course in an academic subject (and vice versa). These tradeoffs are not captured in the first two measures. The third measure accommodates the zero-sum nature of class schedules by calculating the percentage of total courses that are occupational: total occupational credits / (total occupational credits + total academic credits) * 100. This measure is the transverse of the percentage of total courses that are academic, and the reported findings can be alternatively interpreted as an opposite effect of it. Examining both sets of coursetaking measures alongside one another allows for a more comprehensive assessment of the role of coursetaking in improving mathematics proficiency.

The second set measures two specific types of academic and occupational credits earned: (1) academic mathematics, a subset of academic courses; and (2) science, technology, engineering, and mathematics, a subset of occupational education courses herein referred to as OE/STEM courses. The former includes courses that are part of a standard mathematics curriculum such as algebra, geometry, and calculus. The latter includes occupationally focused courses that incorporate quantitative skills, logic, and problem solving. Examples of such courses include mechanical drawing, electronic technology, automotive design, industrial production technology, and computer-assisted design/drafting. Based on these courses, three variables are constructed: (1) the number of Carnegie units earned in academic math courses, (2) the number of Carnegie units earned in OE/STEM courses, and (3) the percentage of Carnegie units earned in quantitative areas that are OE/STEM courses. The last measure is constructed as follows: total OE/STEM credits / (total OE/STEM credits + total academic mathematics credits) * 100.[17]

To be included in the fixed-effects model, which only provides parameter estimates for time-varying variables, each of these measures is summed within two overlapping time periods:

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[16] Note that the denominator includes only academic and occupational courses to measure "total" courses. The other two types of courses—enrichment/other and special education courses—comprise only a marginal number of courses in the average student's schedule. The findings presented in this report are unaffected whether or not these courses are included in the denominator. The measure containing only academic and occupational courses in the denominator is used because it more clearly captures time tradeoffs between academic and occupational courses in the student's schedule.

[17] This last measure assumes that an OE/STEM course was substituted for an academic mathematics course. However, an OE/STEM course can potentially substitute for any course in the student's schedule and thus discerning how coursetaking "time tradeoffs" occur is not directly possible.

period 1 (including credits earned up to the time of the BY interview) and period 2 (including credits earned up to the time of the F1 interview). The period 1 measures indicate the total number of credits earned or the percentage of credits earned between the fall semester of the 2000–01 school year and the spring semester of the 2001–02 school year. The period 2 measures indicate the total number of credits earned or the percentage of credits earned between the fall semester of the 2000–01 school year and the spring semester of the 2003–04 school year. The difference between these two time periods represents changes in the total credits earned or changes in the percentage of credits earned over the course of the last 2 years of high school.

The means of these coursetaking measures are presented in table 2. By the end of their sophomore year, students in the sample had earned on average 10 credits in academic courses and 0.8 credits in occupational courses. By the end of their senior year, students in the sample had earned on average 18.9 academic credits and 2.5 occupational credits. While students left high school with 3.6 credits in academic mathematics, OE/STEM courses were far less prevalent. The average student had earned 0.1 OE/STEM credits by the end of his or her senior year.

Table 2. Summary statistics for variables in the math achievement analysis

	Spring 2001–02 school year		Spring 2003–04 school year	
	Mean	Standard deviation	Mean	Standard deviation
Independent variables				
Total cumulative academic credits earned	10.00	2.00	18.90	3.40
Total cumulative occupational credits earned	0.80	0.90	2.50	2.00
Cumulative percent occupational credits earned	6.60	6.80	10.00	7.70
Total cumulative academic math credits earned	2.00	0.60	3.60	0.80
Total cumulative OE/STEM credits earned	0.10	0.20	0.10	0.50
Cumulative percent OE/STEM credits earned	2.20	7.70	2.90	7.90
Dependent variables				
Number-right score	46.20	12.10	50.60	12.50
Level 1	0.93	0.15	0.96	0.10
Level 2	0.72	0.35	0.79	0.32
Level 3	0.52	0.40	0.63	0.40
Level 4	0.24	0.31	0.36	0.36
Level 5	0.01	0.06	0.04	0.13

N = 7,160

Level 1—simple arithmetical operations on whole numbers, such as simple arithmetic expressions involving multiplication or division of integers; Level 2—simple operations with decimals, fractions, powers, and roots, such as comparing expressions, given information about exponents; Level 3—simple problem solving, requiring the understanding of low-level mathematical concepts, such as simplifying an algebraic expression or comparing the length of line segments illustrated in a diagram; Level 4—understanding of intermediate-level mathematical concepts and/or multistep solutions to word problems such as drawing an inference based on an algebraic expression or inequality; and Level 5—complex multistep word problems and/or advanced mathematics material such as a two-step problem requiring evaluation of functions.

Exhibit reads: By the 2001–02 school year, students in the sample had earned an average of 10 credits in academic courses. In the 2001–02 school year, students in the sample answered an average of 46.20 questions correctly on the mathematics assessment. In the 2001–02 school year, 52 percent of students in the sample were proficient at level 3.

In addition to the key predictor variables, six sets of time-varying control variables are included in the multivariate analyses: survey year, student’s time use, student’s orientation toward school, self-efficacy in math, parental involvement, and grade retention. The first is a binary variable indicating whether the data are from the BY or F1 interview. This measure controls for any natural growth in mathematics that can be attributed to maturation between the two waves of the study. The second is a set of three binary measures that indicate whether the student spends time outside of school on mathematics homework, participating in extracurricular activities, and working for pay. The third is a set of measures that gauge students' orientation toward school based on questions that asked students whether they thought getting a good education was important and how far in school they expected to go. The fourth is a composite based on a series of questions asked to students regarding their beliefs in their ability to do well in math. The fifth is a composite measure indicating the extent to which students discuss academic matters with their parents. The sixth is a binary variable indicating whether the student had been held back a grade between the BY and F1 interviews. The coding of all these variables, including techniques used to address missing data, is included in appendix A. Because they are not central to the research questions posed in this analysis, and because of the volume of literature that examines their relationship to achievement, these variables are used simply as controls; they are not reported in the main body tables or reviewed in the discussion.

Dependent Variables

The key dependent variable in this section is mathematics achievement. Cognitive assessments in mathematics were administered to students in their schools during the BY and F1 survey administrations. These tests, designed and scored using Item Response Theory (IRT), serve as "bookends" to learning that took place during the 2002–03 and 2003–04 academic years—that is, approximately the end of sophomore year to approximately the end of senior year for on-time students. These assessments were designed to maximize the accuracy of measurement that could be achieved in a limited amount of testing time while minimizing floor and ceiling effects, by matching sets of test questions to initial estimates of students' achievement. For this analysis, six measures of mathematics achievement based on performance on this test are used: an estimated number-right score and five proficiency probability scores. All six are derived from performance on the same test and, hence, are not independent measures.

The estimated number-right score is an overall measure of mathematical knowledge and skill, and indicates the number of items an examinee would have answered correctly if he or she had taken all 81 items in the item pool on the multiform assessment administered to 10th-graders in ELS:2002's predecessor study, the National Education Longitudinal Study of 1988 (NELS:88). These scores in ELS:2002 are not integers because they are sums of probabilities. For practical purposes, however, they can be substantively interpreted as the number of items answered correctly. For ease of expression, we refer to this as "number-right" score throughout. On average, students in the sample answered 46.2 questions correctly on the mathematics assessment at the end of their sophomore year and 50.6 questions correctly at the end of their senior year (table 2).

A proficiency probability score is a criterion-referenced score indicating mastery of specific skills and knowledge. Five distinct scores correspond to five hierarchical levels (level 1 through level 5). Mastery of a higher level typically implies proficiency at lower levels. In contrast to the estimated number-right scores, which indicate overall achievement, the proficiency probability scores indicate what knowledge and skills the student does or does not possess. The five ordinal levels of mathematics proficiency include the following:

1. simple arithmetical operations on whole numbers, such as simple arithmetic expressions involving multiplication or division of integers;
2. simple operations with decimals, fractions, powers, and roots, such as comparing expressions, given information about exponents;
3. simple problem solving, requiring the understanding of low-level mathematical concepts, such as simplifying an algebraic expression or comparing the length of line segments illustrated in a diagram;
4. understanding of intermediate-level mathematical concepts and/or multistep solutions to word problems such as drawing an inference based on an algebraic expression or inequality; and
5. complex multistep word problems and/or advanced mathematics material such as a two-step problem requiring evaluation of functions.

The proficiency probability score at each level is a continuous measure ranging from 0 to 1 (0 = nonmastery, 1 = mastery). The scores can be interpreted two ways: at the individual level or at the group level. At the individual level, the score indicates the likelihood that a student has mastered the requisite skills and knowledge defined for that proficiency level. At the group level, it indicates the proportion of the group that has mastered the skills and knowledge defined for that proficiency level. For example, the mean level 3 proficiency probability score for students in the analytic sample at the end of 10th grade is 0.52 (table 2). At the individual level, the interpretation is that the average student by the end of 10th grade has a 0.52 chance of being proficient at level 3. At the group level, the interpretation is that by the end of 10th grade, 52 percent of the sample is proficient at level 3.[18] For the purposes of presentation and discussion, throughout this report level 1 is considered basic skills, levels 2 and 3 are considered intermediate skills, and levels 4 and 5 are considered advanced skills. Further details about the test administration, scoring procedures, the estimated number-right score, and the proficiency probability scores are provided in appendix A.

As shown in table 2, the greatest improvements in math achievement during the 11th and 12th grades occurred at levels 3 and levels 4. Over the last 2 years of high school, the percentage of students proficient at level 3 improved by about 11 percentage points (from 52 percent to 63 percent) and the percentage of students proficient at level 4 improved by about 12 percentage points (from 24 percent to 36 percent). By the end of senior year, nearly the entire sample was proficient at the most basic level (96 percent at level 1) and very few were proficient at the most advanced level (4 percent at level 5). These values are close to 100 and to 0 by design as a means to prevent ceiling and floor effects.

[18] On the interpretation of a probability as a proportion, see Fleiss, Levin, and Paik (2003, p. 1).

Analytic Direction

The math achievement analysis has four main components. The first is a bivariate analysis depicting the relationship between occupational coursetaking and the six test scores (table 3). This provides a descriptive overview of achievement by different coursetaking patterns. The second part estimates the effect of coursetaking on achievement using fixed-effects regression (tables 4–5). The third part extends the fixed-effects regression models by including interaction terms to examine whether occupational coursetaking differentially affects the learning gains of economically disadvantaged students, nonnative English speaking students, and racial/ethnic minorities. Additionally, interaction terms are used to assess whether occupational coursetaking has more bearing on achievement for boys or for girls, has stronger effects during the first or second half of high school and whether occupational coursetaking differentially affects the learning gains of students who enter the second half of high school with varying levels of math proficiency (table 6). The last section examines whether occupational courses that incorporate quantitative skills and concepts influence learning beyond what is gained from traditional academic mathematics courses (tables 7–8).

Findings

Table 3 reports mean 12th-grade test scores by students' cumulative coursetaking histories through the spring of 2003–04. Not surprisingly, the highest test scores were posted by students who had earned a large number of academic credits. Students who earned 26 or more academic credits answered 62 questions correctly on the mathematics assessment and, with the exception of the most advanced level (level 5), the majority of these students were proficient in basic, intermediate, and advanced skills and concepts. Patterns related to occupational coursetaking mirror those depicted in other national analyses: on average, students who take a larger number of occupational courses have lower scores on the mathematics assessment than their peers who take fewer occupational courses (Ingels, Planty, and Bozick 2005; Levesque, Lauen, Teitelbaum, Alt, and Librera 2000). For example, students who have earned three occupational course credits answered on average about 50 questions correctly, while those who earned no occupational courses credits answered about 55 questions correctly. By and large, this overall finding holds when assessing different skill levels. For example, 32 percent of students who earned credit in three occupational courses were proficient at level 4—understanding of intermediate-level mathematical concepts and/or multistep solutions to word problems—compared with 51 percent of their peers who did not take any occupational courses.

Table 3. 12th-grade math achievement scores by total credits earned in high school

	Number-right score	Proficiency probability scores					N
		Level 1	Level 2	Level 3	Level 4	Level 5	
Total occupational credits earned							
0	55.0	0.96	0.84	0.74	0.51	0.08	1,003
1	52.0	0.97	0.81	0.66	0.40	0.05	1,568
2	50.7	0.96	0.79	0.64	0.36	0.04	1,485
3	49.9	0.97	0.79	0.62	0.32	0.04	1,106
4	49.4	0.96	0.77	0.60	0.32	0.04	721
5+	46.2	0.95	0.71	0.51	0.23	0.01	1,277
Total academic credits earned							
0–15	41.0	0.91	0.57	0.34	0.14	0.01	1,171
15–20	48.6	0.96	0.76	0.58	0.29	0.02	3,336
21–25	56.9	0.99	0.91	0.81	0.53	0.07	2,296
26+	61.7	1.00	0.96	0.89	0.68	0.15	357
Percent occupational credits earned							
Low	53.6	0.97	0.83	0.71	0.45	0.06	2,879
High	48.5	0.95	0.75	0.58	0.29	0.03	4,281
Total OE/STEM credits earned							
0	50.3	0.96	0.78	0.62	0.35	0.04	6,300
1	51.7	0.97	0.81	0.64	0.38	0.05	656
2+	54.6	0.98	0.86	0.76	0.49	0.04	204
Total academic math credits earned							
0–2	41.7	0.92	0.59	0.37	0.14	0.00	647
3	46.3	0.95	0.72	0.52	0.23	0.01	2,306
4	53.5	0.97	0.85	0.72	0.43	0.05	2,938
5+	57.4	0.98	0.88	0.78	0.56	0.11	1,269
Percent OE/STEM credits earned							
Low	50.3	0.96	0.78	0.62	0.35	0.04	6,283
High	52.3	0.97	0.82	0.67	0.40	0.05	877

N = 7,160

Level 1—simple arithmetical operations on whole numbers, such as simple arithmetic expressions involving multiplication or division of integers; Level 2—simple operations with decimals, fractions, powers, and roots, such as comparing expressions, given information about exponents; Level 3—simple problem solving, requiring the understanding of low-level mathematical concepts, such as simplifying an algebraic expression or comparing the length of line segments illustrated in a diagram; Level 4—understanding of intermediate-level mathematical concepts and/or multistep solutions to word problems such as drawing an inference based on an algebraic expression or inequality; and Level 5—complex multistep word problems and/or advanced mathematics material such as a two-step problem requiring evaluation of functions.

Exhibit reads: Students in the sample who had earned one occupational credit answered an average of 52 questions correctly on the mathematics assessment. Sixty-six percent of students in the sample who had earned one occupational credit were proficient at level 3.

To describe the relationship between achievement and the percentage of courses that are occupational, the continuous percentage variable was dichotomized at the median (low, high). The patterning by and large is similar to the total credit measures. For example, students who took a high percentage of occupational courses (or a low percentage of academic courses) answered about 49 questions correctly on the mathematics assessment while those who took a low percentage of occupational courses (or a high percentage of academic courses) answered about 54 questions correctly on the mathematics assessment. In terms of proficiency levels, those with a lower percentage of occupational courses are more proficient than their peers with a high percentage of occupational courses at all levels. The differences between high and low are most pronounced at level 3 (difference = 0.13) and level 4 (difference = 0.16).

While in the aggregate occupational courses show a negative relationship to test scores, this is not the case for all types of occupational courses. OE/STEM courses, a subgroup of all occupational courses, incorporate quantitative skills, logic, and problem solving. The content of these occupational courses should align more closely with the content on the test than occupational courses as a whole. The evidence here suggests that this might be the case: students who earned two or more OE/STEM credits answered 55 questions correctly, while students who did not earn any OE/STEM credits answered 50 questions correctly. Moreover, almost half of students (49 percent) who earned three or more OE/STEM credits were proficient at level 4 compared with 35 percent of their peers who did not earn any OE/STEM credits. Although the differences are modest, those who took a high percentage of OE/STEM courses (relative to the total number of quantitative courses) answered more questions correctly on the mathematics assessment and are more proficient at all levels than their peers who took a low percentage of OE/STEM courses.

Since observational data are used here with simple bivariate statistics, these associations cannot be used to evaluate the *effect of CTE* on achievement. The relationships in table 2 may reflect the types of students who follow different curricular pathways and the types of schools these students attend rather than the true effects of the courses themselves. Therefore, to obtain the best estimate of the causal effect of CTE coursetaking, fixed-effects regression is used.

The fixed-effect approach used in this analysis has three advantages. First, fixed-effects regression models only analyze within-student variation over time and, therefore, time-invariant characteristics of students such as sex, race/ethnicity, personality or temperament, innate ability, and genetic makeup as well as period-invariant characteristics such as the structure of state education agencies are effectively held constant. As a result, any potential bias owing to the differential placement of students into curricular programs (i.e., affluent, academically engaged students placed in academic courses and disadvantaged, academically disengaged students placed in occupational courses) is removed.

Second, time-varying measures of student time use, orientations toward schooling, self-efficacy in math, parental involvement, and grade retention are included as controls. As students' plans for the future change, so do their investments in school and work. If students become disinterested in their academic coursework and/or plan to forgo college after high school to directly enter the workforce, they may enroll in fewer academically challenging courses and begin taking more occupationally relevant courses. Under this scenario, any estimated effect of occupational courses may reflect changes in youths' orientations to school and to work rather than the true effect of coursework. Including these time-varying controls helps guard against this possibility.

Third, all models include a binary indicator of the survey year (“1” = 2003–04 school year or BY interview; “0” = 2001–02 school year or F1 interview) for each student and, thus, the estimates are not confounded by any natural growth in mathematics skill that may occur between the test administrations (e.g., students simply getting better at mathematics over time). With broad classes of potential confounds eliminated, the models presented here provide a rigorous test of the effect of CTE courses on learning. More information on this modeling approach is contained in appendix A.

Table 4 shows the results for six fixed-effects regression models. Each model contains an estimate for the number of academic courses and the number of occupational courses taken during the last 2 years of high school. The first column shows estimates from a model predicting the number-right score. This is akin to the aggregate subject scores used in past research. The next five models estimate the effect of academic and occupational courses on the proficiency probability scores. Table 5 follows the same progression of models, but replaces the total credit measures with the single measure of the percent of courses that are occupational. Additionally, this model includes a control for the total number of courses taken. Parameter estimates for the control variables included in the models are shown in appendix C.[19]

Table 4. Fixed-effects estimates of the effect of total academic and occupational courses on math achievement

		Proficiency probability scores				
	Number-right score	Level 1	Level 2	Level 3	Level 4	Level 5
Total occupational credits earned	-0.096	-0.001	0.001	-0.001	-0.004	-0.001**
	(0.348)	(0.002)	(0.003)	(0.006)	(0.004)	(0.000)
Total academic credits earned	0.348**	-0.003**	-0.002	0.004**	0.015**	0.009**
	(0.038)	(0.001)	(0.003)	(0.001)	(0.001)	(0.001)

NOTE: Numbers in parentheses are standard errors. All models include controls for survey year, student time use, orientation toward school, self-efficacy in math, parental involvement, grade retention, and missing data.

N = 7,160

* $p < 0.05$

** $p < 0.01$

Level 1—simple arithmetical operations on whole numbers, such as simple arithmetic expressions involving multiplication or division of integers; Level 2—simple operations with decimals, fractions, powers, and roots, such as comparing expressions, given information about exponents; Level 3—simple problem solving, requiring the understanding of low-level mathematical concepts, such as simplifying an algebraic expression or comparing the length of line segments illustrated in a diagram; Level 4—understanding of intermediate-level mathematical concepts and/or multistep solutions to word problems such as drawing an inference based on an algebraic expression or inequality; and Level 5—complex multistep word problems and/or advanced mathematics material such as a two-step problem requiring evaluation of functions.

Exhibit reads: An additional credit earned in an academic course is associated with .348 more questions answered correctly on the mathematics assessment and a .009 increase in the probability of proficiency at level 5.

[19] Although the control variables are not central to the research questions posed in this report, it is interesting to note that a consistent finding across the models is the effect of students’ expectations and their time spent on math homework: Students who expect to receive a college degree and who spend time on their math homework exhibit larger gains in the number-right scores and at the advanced levels (4 and 5).

Table 5. Fixed-effects estimates of the effect of the percentage of courses that are occupational on math achievement

		Proficiency probability scores				
	Number-right score	Level 1	Level 2	Level 3	Level 4	Level 5
Percent occupational credits earned	-0.001**	0.966^{-5}	0.637^{-5}	-0.438^{-5}	-0.343^{-5}**	-0.147^{-5}**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

NOTE: Coefficients are expressed using scientific notation because of the large number of decimals. Numbers in parentheses are standard errors. All models include controls for survey year, student time use, orientation toward school, self-efficacy in math, parental involvement, grade retention, total number of courses, and missing data.

N = 7,160

* $p < 0.05$

** $p < 0.01$

Level 1—simple arithmetical operations on whole numbers, such as simple arithmetic expressions involving multiplication or division of integers; Level 2—simple operations with decimals, fractions, powers, and roots, such as comparing expressions, given information about exponents; Level 3—simple problem solving, requiring the understanding of low-level mathematical concepts, such as simplifying an algebraic expression or comparing the length of line segments illustrated in a diagram; Level 4—understanding of intermediate-level mathematical concepts and/or multistep solutions to word problems such as drawing an inference based on an algebraic expression or inequality; and Level 5—complex multistep word problems and/or advanced mathematics material such as a two-step problem requiring evaluation of functions.

Exhibit reads: A 1 percent increase in the percentage of courses that are occupational is associated with .001 fewer questions answered correctly on the mathematics assessment and a $.147^{-5}$ decrease in the probability of proficiency at level 5.

The total number of occupational credits earned during the last 2 years of high school has no relationship to the number of correct answers on the mathematics assessment. However, when occupational courses comprise a larger percentage of the total number of courses taken, students answer fewer questions correctly on the mathematics assessment.

The model predicting the number-right score in table 4 shows that controlling for academic coursetaking, survey year, time use, orientations toward school, self-efficacy in math, parental involvement, grade retention, time-invariant characteristics, and period-invariant characteristics, the total number of occupational courses taken is unrelated to the number of questions answered correctly on the mathematics assessment. This corroborates earlier research using NELS:88 that finds no association between Carnegie units in vocational courses and overall learning gains in mathematics (Rasinksi and Pedlow 1998). However, each additional academic course is associated with more than a third of a correct answer increase on the test. While the *total* number of occupational courses is unrelated to the number-right score, table 5 shows that the *percentage* of courses that are classified as occupational is negatively related with the number-right score. In other words, when occupational courses comprise a larger percentage of the total number of courses taken, students answer slightly fewer questions correctly on the mathematics assessment. A 1 percent increase in the percentage of the total courses in a student's schedule that are classified as occupational is associated with 0.1 fewer questions answered correctly on the mathematics assessment.

Credits earned in occupational courses taken in the last 2 years of high school do not limit gains in basic and intermediate mathematics skills and concepts.

While the model predicting number-right scores in table 5 shows a negative relationship between occupational coursetaking and achievement gains in mathematics, it is not clear what skills and concepts are affected. The coefficients from the models predicting the proficiency probability scores help to elucidate this relationship. Recall that the bivariate relationships in table 3 show that students who take a large number of occupational courses and/or whose class schedules are composed of a large percentage of occupational courses have lower levels of proficiency in mathematics at the intermediate level than their peers who are less invested in occupational courses. This relationship could reflect the true effect of occupational courses on mathematics achievement *or* it could be due to other factors: the types of students who take occupational courses, for example, or the tradeoff between academic and occupational courses. If it is either of the latter, then the bivariate patterning likely distorts the magnitude of learning gains directly attributable to a CTE curriculum. In the fixed-effects models, which remove the potentially confounding effects of academic coursetaking, survey year, time use, orientations toward school, self-efficacy in math, parental involvement, grade retention, time-invariant characteristics, and period-invariant characteristics, none of the occupational coursetaking coefficients for levels 1, 2, and 3 are significantly different from zero (tables 4 and 5). This holds when considering either the total number of occupational courses or the percentage of courses that are occupational. This null finding suggests that the negative bivariate relationships detected in table 3 are spurious and that occupational courses taken in the last 2 years of high school *do not* limit gains in basic and intermediate mathematics skills.

Taking more occupational courses and fewer academic courses during the last 2 years of high school limits the acquisition of advanced mathematics skills and concepts.

Levels 4 and 5 represent the most advanced skills and concepts on the ELS:2002 mathematics assessment. Not surprisingly, academic coursetaking is positively related to learning gains at these levels. The coefficients for total academic courses taken are positive and significant (table 4): all else being equal, each additional academic course is associated with a 0.015 increase in the probability of proficiency at level 4 and a 0.009 increase in the probability of proficiency at level 5. Conversely, the coefficient for total occupational courses is negative and significant at level 5 (table 4): all else being equal, each additional occupational course is associated with a 0.001 decrease in the probability of proficiency at the most advanced level.

Because academic coursetaking has a positive effect on learning gains at both of the advanced levels and occupational coursetaking has no effect at level 4 and a negative effect at level 5, it is likely that supplanting academic courses with occupational courses will impede the acquisition of the most advanced mathematics skills and concepts. The findings in table 5 support this contention. The larger the percentage of occupational courses in one's course schedule, the lower the gains at these levels.

To get a sense of the magnitude of these effects, predicted 12th-grade number-right scores and proficiency probability scores based on the coefficients from the models in table 5 are shown in figure 1 and figure 2. Each predicted score assumes the student left 10th grade with an average score on the BY assessment and has average values on the measures of time use, orientation toward school, self-efficacy in math, parental involvement, and experienced no grade retention between the BY and F1 interviews. Each figure displays the predicted scores for three sets of students following different coursetaking patterns during the last 2 years of high school:

- The first coursetaking pattern is that of the average student. This pattern assumes that 15.2 percent of the student's course schedule was composed of occupational courses during the last 2 years of high school (8.9 academic courses and 1.6 occupational courses)—the average coursetaking pattern for public school students in ELS:2002.

- The second coursetaking pattern in the cluster is for students whose course schedule was 28.6 percent occupational in the last 2 years of high school (8.5 academic courses and 2 occupational courses)—by NCES criteria, an occupational concentrator. Approximately 36 percent of the analytic sample met these criteria.

- The final coursetaking pattern in the cluster is for students whose course schedule was 0.0 percent occupational in the last 2 years of high school (10.5 academic courses and 0 occupational courses), essentially substituting the 3 occupational credits from the second bar for 3 academic credits—by NCES criteria, an academic concentrator. Approximately 14 percent of the analytic sample met these criteria.

Figure 1. Predicted 12th-grade number-right scores by coursetaking patterns

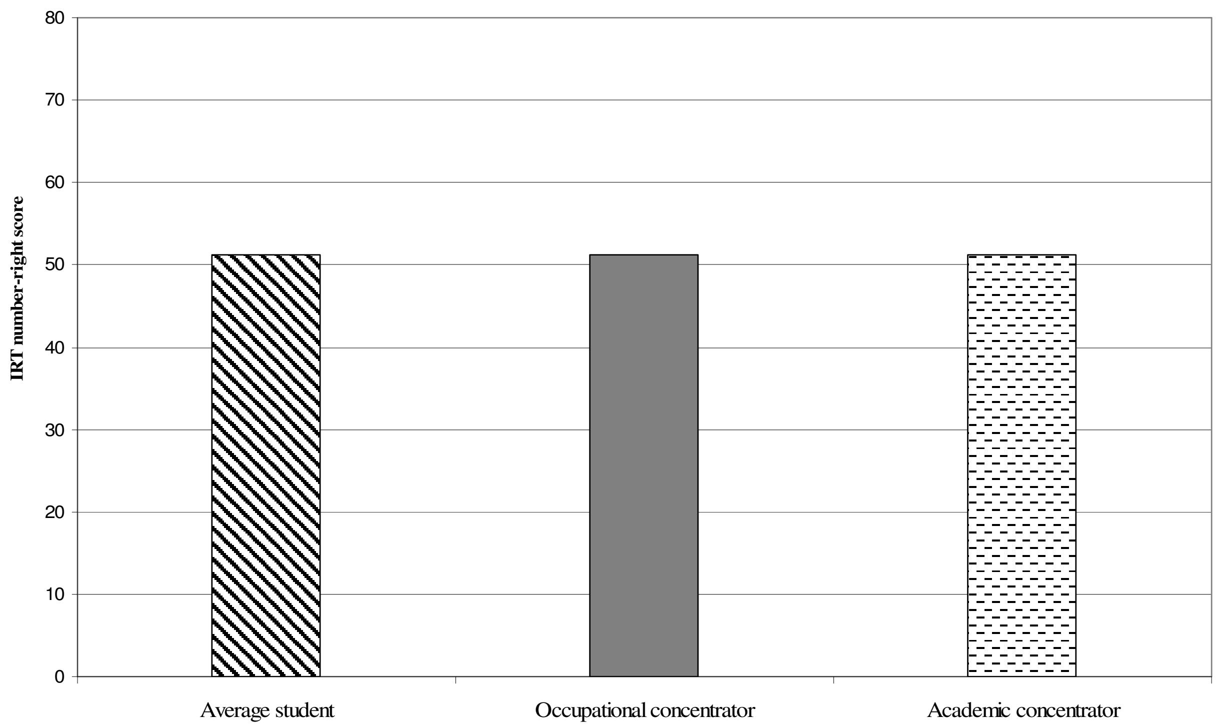
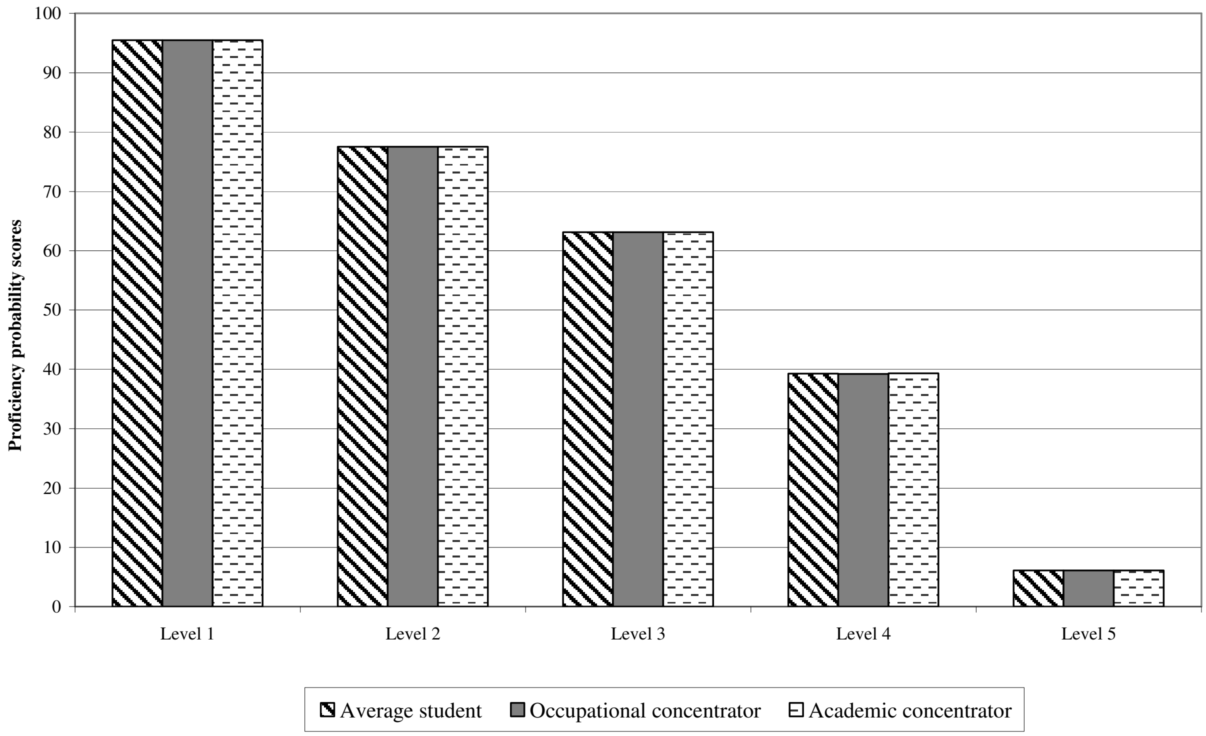


Exhibit reads: Students classified as occupational concentrators are predicted to answer an average of 51 questions correctly on the 12th-grade mathematics assessment.

Figure 2. Predicted 12th-grade proficiency probability scores by coursetaking patterns



Level 1—simple arithmetical operations on whole numbers, such as simple arithmetic expressions involving multiplication or division of integers; Level 2—simple operations with decimals, fractions, powers, and roots, such as comparing expressions, given information about exponents; Level 3—simple problem solving, requiring the understanding of low-level mathematical concepts, such as simplifying an algebraic expression or comparing the length of line segments illustrated in a diagram; Level 4—understanding of intermediate-level mathematical concepts and/or multistep solutions to word problems such as drawing an inference based on an algebraic expression or inequality; and Level 5—complex multistep word problems and/or advanced mathematics material such as a two-step problem requiring evaluation of functions.

Exhibit reads: Approximately 63 percent of students classified as occupational concentrators are predicted to be proficient at level 3 in the 12th grade.

Note that the bars do not represent the actual scores of students following different coursetaking patterns, but rather what the average student is predicted to learn from the courses themselves—apart from any time- and period-invariant factors that select them into different curricula, any observed changes in their time use, orientations toward school, self-efficacy in math, parental involvement, and grade retention during the last 2 years of high school that may affect their motivation to learn, and any natural improvement in mathematics knowledge between the two survey administrations.

The effects of CTE coursetaking on math achievement are <u>modest</u>. Students who earn two or fewer occupational credits in the last 2 years of high school learn as much in mathematics from their coursework as do students who earn only academic credits.

Figure 1 compares the predicted scores for the average number-right scores for students following different coursetaking patterns during the last 2 years of high school. Although the coefficient for "Percent occupational courses" in model 4 indicates that a larger percentage of occupational courses is associated with fewer questions answered correctly, the magnitude of this effect, as evidenced by the predicted scores in figure 1, is small. All three coursetaking patterns result in nearly identical predicted scores: All else being equal, students taking an average number of academic and occupational courses would answer 51.3 questions correctly, occupational concentrators would answer 51.2 questions correctly, and academic concentrators would answer 51.3 questions correctly. This suggests that in terms of overall performance on the mathematics assessment, substituting two occupational courses for two academic courses does not hinder achievement.

To assess the specific types of skills and concepts used, coefficients from the models predicting the proficiency probability scores (table 5) are used. The predicted scores for the different coursetaking patterns are shown in figure 2. Recall that the proficiency probability scores can be interpreted at the group level—in this example, the groups are students following different coursetaking patterns. As an illustration, the first bar in the level 1 cluster indicates that 96 percent of students would be proficient at level 1 by the end of 12th grade if they followed an average coursetaking pattern in the last 2 years of high school. With this interpretation in mind, the average student leaves high school with solid mastery of basic skills, moderate mastery of intermediate skills (78 percent at level 2 and 63 percent at level 3), and a low mastery of advanced skills (39 percent at level 4 and 6 percent at level 5). This accords with national trends estimated using the full ELS:2002 sample (Ingels, Planty, and Bozick 2005).

The main effects estimates in table 5 indicate that course schedules with a greater percentage of occupational courses are associated with lower levels of proficiency in the advanced levels. The magnitude of these effects, much like those in the number-right score analysis, are very small. When comparing the scores of students following the different coursetaking patterns, differences within all levels, *including the advanced levels*, are negligible. For example, at level 4, the predicted proficiency probability score for a student taking three occupational courses is the same as the predicted proficiency probability score for a student taking zero occupational courses (0.39). This indicates that all things being equal, a student who became an occupational concentrator in the last 2 years of high school would have approximately the same mastery of level 4 skills and concepts as the student who enrolled in all academic courses during the same time period.

On the whole, the effects detected in the fixed-effects regression analysis are extremely small: students who take two or fewer occupational courses in the last 2 years of high school learn as much in mathematics from their coursework as do students who take all academic courses. Thus, any concern that occupational courses will supplant learning in mathematics should be assuaged.[20] A word of caution in interpreting these findings: as evidenced in table 2 and in other similar studies (see Ingels, Planty, and Bozick 2005; Levesque, Lauen, Teitelbaum, Alt, and Librera 2000), large achievement differences *do exist* between students who take a mostly occupationally focused curriculum and students who take an academically focused curriculum. However, what the present analysis shows is that *these differences are not attributable to the courses themselves*, but likely to the characteristics of the students who take them.

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[20] In preliminary analyses not shown, the fixed-effects models shown in table 4 were estimated without the variable measuring the number of academic courses. In these models, occupational courses yielded a significant negative effect on the IRT number-right score, the level 4 score, and the level 5 score. As shown in table 3, when academic courses are included, the effect of occupational courses on the number-right score and the level 4 score disappears and the coefficient for the level 5 score is reduced but remains significant. This provides additional evidence that any negative effect of occupational coursetaking is largely accounted for by academic coursetaking.

Occupational courses have similar effects on aggregate math achievement for both poor and nonpoor students as well as nonnative English speakers and native English speakers. Black and Asian students benefit more from occupational courses than do White students.

Do these effects vary across the three No Child Left Behind (NCLB) subgroups (economically disadvantaged students, nonnative English-speaking students, and racial-ethnic minorities)? Do boys benefit more or less than girls from taking occupational courses? Are these effects stronger during the first half of school or the last half? Do low-achieving students benefit more or less than their high-achieving peers from taking occupational courses? To assess these questions, interactive analyses were conducted.[21] First, each of the variables representing the three NCLB subgroups, sex, the survey year indicator, and the BY test score were multiplied by the coursetaking terms. Then, two sets of interactive models were estimated. The first set included interactions for total academic courses and total occupational courses. Since the focus here is on occupational coursetaking, the findings for academic courses are not shown. This first set included 36 fixed-effects regression models: six dependent variables times six sets of interaction terms corresponding with the NCLB groups, sex, the survey year indicator, and the 10th-grade math achievement score equals 36 models. The second set of models replaced the total coursetaking interaction terms with interaction terms using the percentage of courses that are classified as occupational. Since interpreting each of the coefficients across multiple models is tedious, the results from all the models are summarized in table 6. The results from the first set appear in the “Total” column and the results from the second set appear in the “%” column. The signs (+/-) represent the effect on achievement: a single sign indicates a significant effect at $p < 0.05$ and a double sign indicates a significant effect at $p < 0.01$. Empty cells indicate that there was no significant difference in the main effect between the two groups.

[21] As time-invariant predictors, the main effects associated with the NCLB subgroups, sex, and BY test scores cannot be estimated, but they can condition the effects of the model’s time-varying predictors (see Allison 1994).

Table 6. Differences in the relationship between occupational coursetaking and mathematics achievement scores across No Child Left Behind subgroups, sex, survey year, and base-year math achievement levels

	Number-right score		Proficiency probability scores: Level 1		Level 2		Level 3		Level 4		Level 5	
	Total	%	Total	%	Total	%	Total	%	Total	%	Total	%
Main effect		—								—	—	—
Economic disadvantage												
Poor vs. not poor				++						-	++	—
Limited English proficiency												
Nonnative English speaker vs. native English speaker						+				—	—	
Racial-ethnic groups												
Black vs. White	++	+	++	++	++	++				—	++	—
American Indian vs. White	-					+				—		-
		+										
Asian vs. White	++	+			++	++	+	++	++	++	—	
Hispanic vs. White	+					+				—		—
More than one race vs. White		+					—					
Sex												
Males vs. Females												
Survey year												
2003–04 vs. 2001–02	—	—	—		—					—		—
Base-year math achievement levels												
Test score in 10th grade	++	+	++	++	++	++	++	++	++	++	++	++

NOTE: Total = model with total occupational courses as the main effect.
% = model with percent occupational courses as the main effect.
+ or - indicates the p-value associated with the coefficient was less than 0.05.
++ or — indicates the p-value associated with the coefficient was less than 0.01.
Exhibit reads: Compared with White students, the negative relationship between the percentage of courses that are occupational and the number-right score is "less pronounced" or "less negative" for Black students, Asian students, and students who report having more than one race.

The first row summarizes the main effect of occupational coursetaking detected in table 4 and in table 5; remaining rows report the interaction effects. To interpret the interaction effects, take as an example the comparison poor versus not poor. At level 1, the interaction with percentage of courses that are occupational is positive and significant at $p < 0.01$. This indicates that while the average student does not acquire basic mathematics skills from taking occupational courses, poor students benefit *more* than nonpoor students. With that orientation, the layout of table 6 is straightforward.

In terms of overall performance on the assessment (the “number-right” column), poor students are no more or less likely to benefit from occupational courses than their nonpoor peers. Similarly, nonnative English speakers are no more or less likely to benefit from occupational courses than their native English speaking peers. There is, however, evidence of differential effects across racial/ethnic groups. Black and Asian students benefit more from occupational courses than their White peers—the interaction terms are significantly different from zero in both the “Total” and the “%” models for these groups. Additionally, there is some evidence that when compared with their White peers, Hispanic and multiracial students benefit more and American Indian students benefit less from occupational courses. However, these interactions are not significant in both sets of models.

Across the proficiency probability scores (“Level 1” through “Level 5” columns), the effects of occupational courses are on average the same for poor/nonpoor students and nonnative English speakers/native English. None of the interactions for these subgroups yield significant interactions in both the “Total” and the “%” models at one level. In terms of racial-ethnic minorities, Black students and Asian students appear to benefit most from occupational courses. For Black students, the interactions in both the “Total” and “%” models at levels 1 and 2 are positive and significant, indicating that occupational courses have a greater boost for Black students than for White students at these levels. In other words, if Black and White students both take an equal number of occupational courses, gains in proficiency at level 1 would be significantly higher for Black students than for White students. For Asian students, the interactions in both the “Total” and “%” models at levels 2, 3, and 4 are positive and significant, indicating that occupational courses have a greater boost for Asian students than for White students at these levels.

It is interesting to note that at level 5, some of the findings are inconsistent or contradictory. For example, the coefficient for the poor versus not poor contrast is significant and positive in the “Total” model, but significant and negative in the “%” model. Similarly, the coefficient for the Black versus White contrast is significant and positive in the “Total” model, but significant and negative in the “%” model. Given the small percentages of students who are proficient at this level (1 percent in the BY interview and 4 percent in the F1 interview), the stringent controls used, and the relatively small size of the NCLB subgroups in the overall sample, the interaction terms are likely to produce erratic results. The findings at this level are potentially unstable and, therefore, they are presented but not discussed here.

On the whole, it appears that occupational courses have similar effects for both poor and nonpoor students as well as nonnative English speakers and native English speakers. However, two racial-ethnic minority groups, Blacks and Asians, benefit more from occupational courses than do White students. Specifically, Blacks benefit more at level 1, level 2, and in the overall number of questions answered correctly. Asians benefit more at level 2, level 3, level 4, and the overall number of questions answered correctly. Any concern that the NCLB subgroups might be systematically affected and/or disadvantaged by enrollment in occupational courses is not supported in this analysis. Also, any concern that males and females are at a greater/lesser risk due to their involvement in CTE is not supported here: none of the interactions involving sex yielded significant coefficients.

Occupational coursetaking is more likely to impede achievement in mathematics during the second of half of high school than the first.

The penultimate row in table 6 tests the consistency of effects across the survey years. A significant positive interaction indicates that occupational coursetaking is more likely to enhance mathematics achievement on the senior year assessment than the sophomore year assessment while a significant negative interaction indicates that occupational coursetaking is more likely to enhance performance on the sophomore year assessment than the senior year assessment. Across the models, it appears that the latter is the case. In terms of overall performance, the "Total" and "%" interactions in the number-right score models are both negative and significant at $p < 0.01$. In terms of proficiency at different skill levels, the "Total" interactions at levels 1 and 2 and the "%" interactions at levels 4 and 5 are all negative and significant at $p < 0.01$. Together, these suggest that occupational coursetaking is more likely to impede achievement in mathematics during the second of half of high school than the first.

Occupational coursetaking is less likely to impede the achievement of students who are initially high achievers in math.

The last row in table 6 tests the consistency of effects across initial levels of math achievement. A significant positive interaction indicates that occupational coursetaking is more likely to enhance learning among students who are already proficient in math while a significant negative interaction indicates that occupational coursetaking is more likely to depress the gains of students who are already proficient in math. In every model, the interactions are positive and significant at $p < 0.01$. Since the main effect of the number-right score and levels 4 and 5 are negative, these interactions suggest that high achievers are "buffered" from any negative effect of occupational courses. In other words, occupational coursetaking is less likely to impede the achievement of students who are initially high achievers in math.

Improving learning in mathematics is largely a function of traditional academic mathematics courses. However, OE/STEM in the CTE curriculum may impede learning at the most advanced levels if they are taken in place of regular academic math courses.

The mathematics achievement analysis concludes with a look at occupational courses that are most likely to develop quantitative skills. As discussed earlier, standardized achievement tests do not capture the breadth of concepts and skills taught in most occupational courses. Consequently, they are not the best instrument to assess learning in a CTE curriculum. However, some occupational courses incorporate quantitative skills, logic, and problem solving. In theory, these courses should yield greater achievement gains than occupational courses that do not cover these topics. To test this proposition, two sets of fixed-effects regression models were estimated. The first set is akin to the estimates presented in table 4, with the measures of occupational credits replaced with the measures of OE/STEM credits and the measures of academic credits replaced with the measures of academic mathematics credits. The parameter estimates are presented in table 7. These models can effectively be considered a test of the efficacy of "occupational mathematics" beyond what is learned in the traditional mathematics curriculum. The second set replaces the total credits earned measure with the credits earned in OE/STEM courses as a percentage of all quantitative courses (academic math courses + OE/STEM courses). Although the zero-sum relationship of these courses is not the same as the academic-occupational tradeoff (i.e., one additional course in OE/STEM does not necessarily mean one fewer academic mathematics course, this measure gauges the integration of quantitatively focused occupation courses into an overall mathematics curriculum). These parameter estimates are presented in table 8.[22]

Table 7. Fixed-effects estimates of the effect of total science, technology, engineering, and mathematics (OE/STEM) courses and academic math courses on math achievement

	Number-right score	Proficiency probability scores: Level 1	Level 2	Level 3	Level 4	Level 5
OE/STEM credits earned	0.015	0.002	-0.009	-0.015	0.012**	0.001
	(0.097)	(0.001)	(0.006)	(0.015)	(0.004)	(0.001)
Academic math credits earned	1.408**	-0.872^{-5}	0.004*	0.019**	0.050**	0.027**
	(0.095)	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)

NOTE: Numbers in parentheses are standard errors. All models include controls for survey year, student time use, orientation toward school, self-efficacy in math, parental involvement, grade retention, and missing data.

N = 7,160

* $p < 0.05$

** $p < 0.01$

Level 1—simple arithmetical operations on whole numbers, such as simple arithmetic expressions involving multiplication or division of integers; Level 2—simple operations with decimals, fractions, powers, and roots, such as comparing expressions, given information about exponents; Level 3—simple problem solving, requiring the understanding of low-level mathematical concepts, such as simplifying an algebraic expression or comparing the length of line segments illustrated in a diagram; Level 4—understanding of intermediate-level mathematical concepts and/or multistep solutions to word problems such as drawing an inference based on an algebraic expression or inequality; and Level 5—complex multistep word problems and/or advanced mathematics material such as a two-step problem requiring evaluation of functions.

Exhibit reads: An additional credit earned in an academic math course is associated with 1.408 more questions answered correctly on the mathematics assessment and a .027 increase in the probability of proficiency at level 5.

[22] Since the measures of quantitative coursetaking used here do not explicitly consider the *level* of courses taken, it is unclear whether the effects of a "time trade-off" are different for youth substituting CTE courses for lower-level math courses than for youth substituting CTE courses for higher-level math courses. As a test, we examined the distribution of OE/STEM courses by the highest math course taken by students. There were no significant differences between the average number of OE/STEM courses taken by students taking higher-level math courses and students taking lower-level math courses. Further, we created a binary variable indicating whether or not the student had taken advanced math courses (ADV). We then created an interaction term OE/STEM * ADV and included it in all models where OE/STEM is estimated as a main effect. In none of the models did this interaction term yield a significant parameter estimate, indicating that the effect of OE/STEM is the *same* for both students taking advanced math courses and students taking lower-level math courses.

Table 8. Fixed-effects estimates of the effect of the percentage of quantitative courses that are science, technology, engineering, and mathematics (OE/STEM) on math achievement

	Number-right score	Proficiency probability scores				
		Level 1	Level 2	Level 3	Level 4	Level 5
% OE/STEM credits earned	-0.028	0.001**	-0.002	-0.002	-0.002**	-0.001**
	(0.016)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)

NOTE: Quantitative courses include academic math courses and occupational math courses. Numbers in parentheses are standard errors. All models include controls for survey year, student time use, orientation toward school, self-efficacy in math, parental involvement, grade retention, total number of quantitative courses, and missing data.

N = 7,160

* p < 0.05

** p < 0.01

Level 1—simple arithmetical operations on whole numbers, such as simple arithmetic expressions involving multiplication or division of integers; Level 2—simple operations with decimals, fractions, powers, and roots, such as comparing expressions, given information about exponents; Level 3—simple problem solving, requiring the understanding of low-level mathematical concepts, such as simplifying an algebraic expression or comparing the length of line segments illustrated in a diagram; Level 4—understanding of intermediate-level mathematical concepts and/or multistep solutions to word problems such as drawing an inference based on an algebraic expression or inequality; and Level 5—complex multistep word problems and/or advanced mathematics material such as a two-step problem requiring evaluation of functions.

Exhibit reads: A 1 percent increase in the percentage of quantitative courses that are OE/STEM is associated with a .001 decrease in the probability of proficiency at level 5.

The evidence in table 7 suggests that academic mathematics courses improve overall mathematics learning. Specifically, each additional academic mathematics course taken during the last 2 years of high school is associated with 1.4 more correct answers on the 12th-grade mathematics assessment. This accords with previous research on coursetaking and mathematics achievement using ELS:2002 (Bozick and Ingels 2008). Additionally, academic mathematics courses improve learning at all levels except level 1. The relationship is strongest at the advanced levels. OE/STEM courses, on the other hand, enhance mathematics learning only at level 4. Each additional OE/STEM course is associated with a 0.012 increase in the probability of proficiency at level 4. OE/STEM courses have no additional effect on the number-right score or proficiency at levels 1, 2, 3, and 5.[23]

Table 8 replaces the total mathematics coursetaking measures with the percentage of quantitative courses that are OE/STEM measures. In this set of models, the coefficients are negative and significant at levels 4 and 5: a percentage point increase in the percentage of quantitative courses taken during the last 2 years of high school that are classified as OE/STEM is associated with a 0.002 decrease in the probability of proficiency at level 4 and a 0.001 decrease in the probability of proficiency at level 5. Although the total occupational course coefficient is positive at level 4, the percent coefficient is negative. This suggests that any

[23] These null findings are surprising given that OE/STEM courses are more aligned with the traditional mathematics content assessed by the test than the rest of the occupational areas. There are several possible reasons for this. First, the quantitative skills and applications learned in OE/STEM courses may complement and/or marginally extend those learned in academic mathematics courses and, therefore, have no *additional* benefit. Second, OE/STEM courses may be replacing academic math courses in some students' schedules, thereby resulting in similar growth in mathematics learning. Third, only a small portion of the sample—approximately 7 percent—had taken an OE/STEM course in the last 2 years of high school. Thus, the standard errors accompanying the OE/STEM coefficients are larger than those for the academic mathematics coefficients, making it difficult to detect an effect if there is one (i.e., a type II error).

positive effect of OE/STEM courses is attenuated if they are not taken alongside regular academic math courses.

Taken together, the evidence here suggests that improving learning in mathematics is largely a function of traditional academic mathematics courses. In general, OE/STEM courses do not compromise learning in math. However, if students are taking OE/STEM courses in place of their regular academic math courses, their mastery of the most advanced skills and topics may be modestly tempered.

III. THE RELATIONSHIP BETWEEN CAREER AND TECHNICAL EDUCATION AND DROPPING OUT OF HIGH SCHOOL

This section addresses the second research question: is career and technical education (CTE) coursework associated with the decision to drop out of high school? As noted, prior research has yielded mixed results when assessing the relationship between CTE coursetaking and dropping out, and has also been compromised by less-than-adequate research designs that have not accounted for the temporal relationship between coursetaking and dropping out as well as the confounding effects of student sociodemographic and academic characteristics. The present analysis addresses timing of measurement issues and possible selection bias simultaneously through the use of event history models. This technique, also called hazard modeling or survival analysis, explicitly examines the dropout rate for each period of time covered by the data, creating estimates that adjust for timing differences in the event of interest—in this analysis, the first episode of dropping out of high school. However, the timing of dropout decisions is still a concern; since some dropout events occur prior to the 10th grade, and the ELS:2002 data follow students from 10th grade on, early dropout behavior cannot be observed (in the parlance of event history modeling, these events are "censored"). According to ELS:2002's predecessor study, the National Education Longitudinal Study of 1988 (NELS:88), which began with 8th-graders instead of 10th-graders, about 6.8 percent of 8th-graders were dropouts by 10th grade, and another 7.6 percent of 10th-graders were dropouts by 12th grade (McMillen and Kaufman 1996). Nevertheless, because most CTE coursetaking takes place in the last 2 years of high school (11th and 12th grades), the relationship between CTE coursetaking and dropping out is likely to be accurately represented in the results presented here.

Sample Selection

The analysis is based on all sample members who were in-school sophomores in the spring of the 2001–02 school year and who had at least one academic year's worth of transcript information; 14,730 sample members met these criteria. These students would have graduated in the spring of 2004 if they maintained on-time grade progression and met graduation requirements. Of the analysis sample members, 230 had inconclusive information on either the reason for leaving high school (i.e., graduating, dropping out, etc.) or the date of withdrawal. Because this information is central to the analysis, these cases were excluded. An additional 40 cases were excluded because they lacked evidence of any academic coursetaking. Of the remaining 14,460 students, 3,170 attended a Catholic or other private school. These were excluded from the analysis. The final analytic sample includes 11,300 public school students who were in-school sophomores in the spring of the 2001–02 school year. An analysis comparing the composition of the analytic sample used here (N = 11,300) with the full spring 2002 sophomore cohort (N = 16,170) finds that they are roughly similar in sociodemographic and academic resources, suggesting that any potential bias due to the imposed sample selection criteria is minimal. The results of this bias analysis are presented in appendix A.

Dependent Variable

The key dependent variable in this analysis is the timing of the first dropout episode. Dropout information is derived from four source variables within the ELS:2002 data: F1EVDROP, F1D19, F1RREASL, and F1RDTLFT. F1EVDROP indicates whether the student had ever dropped out of high school by the time of the F1 interview. Students are considered to have ever dropped out by F1 if they were reported dropouts at the time of the F1 interview or if they had been reported as a dropout in any of the three enrollment status updates.[24] If students were currently dropouts, they were administered a questionnaire that was tailored toward the dropout experience. On this questionnaire, dropouts were asked to report the month and year they first left school. This information is stored in F1D19. Valid date information was obtained for 830 analytic sample members. If their reported dropout date was not obtainable from the interview, then the month and year of their school exit from their school transcripts was used. Transcript exit dates are taken from two variables: F1RREASL and F1RDTLFT. The former indicates the reason the student left school and the latter indicates the month and year. Sample members were considered to be dropouts if their transcripts indicated they had received a GED or had dropped out. Valid dropout date information was obtained for 130 analytic sample members through the transcripts. For 20 dropouts who lacked valid dropout date information from either the student interview or from transcript-indicated leave information, the last semester in which they passed a course—also derived from the transcript file—was used. In sum, 830 dates were obtained from the F1 interview, 130 dates were obtained from high school transcripts when the interview did not have a valid date, and 20 dates were obtained from the last passed semester as indicated in the transcripts. Thus, a total of 990 dropouts are included in the final analytic sample.

Following Agodini and Deke (2004), all dropout dates were calibrated to approximate semesters of an academic school year. This allows courses (existing on a semester basis) to be aligned with dropout dates. All dropout dates from September through January were considered to occur during the fall semester of their respective year, and all dropout dates between February through August were considered to occur during the spring semester of their respective year. Details on this procedure can be found in appendix A. In all cases, one final adjustment was made. Dropout dates were compared with the last semester during which a student passed a course. If a dropout passed a course during the semester in which the interview or transcript indicated he or she left school, the dropout date was changed to the subsequent semester.

For this analysis, the dependent variable is the timing of dropping out of high school, based on the semester in which they exited school. Exposure to the risk of dropping out begins the spring semester of the 2001–02 school year, the semester in which they entered the study, and extends through the spring semester of 2003–04, the semester when they should be graduating if they had progressed through high school on time. Students remain at risk through the fall semester of the 2004–05 school year, which is one semester beyond their expected date of high school graduation. The dependent variable is coded 0 for all semesters in which the student is enrolled and 1 for the semester in which the student dropped out of high school. As is

[24] RTI International contacts participating schools periodically between survey rounds to maintain contact with school administrators and to gather information about sample members' enrollment status.

typical in event history modeling, individuals are removed from the risk set once they drop out (i.e., experience the event); they no longer contribute person-semesters (i.e., observations) to the analysis. Individuals who graduated or were still enrolled by the fall 2004–05 semester are censored. During the entire risk period, approximately 8 percent of the analytic sample dropped out.

Independent Variables

The principal independent variables are CTE coursetaking and the timing variable itself, semester of schooling. As in the mathematics achievement analysis, the CTE coursetaking variables are operationalized two ways: (1) as separate variables for cumulative academic courses and cumulative occupational courses, and (2) cumulative CTE courses as a percentage of total credits earned. In addition, the dropping-out analysis includes a measure of the ratio of cumulative occupational courses to academic courses to replicate the approach and findings of Plank and colleagues (Plank 2001; Plank, DeLuca, and Estacion 2008). In the context of this analysis, “cumulative” is defined as coursetaking up through the previous semester. For example, cumulative academic courses for the fall semester of the 2003–04 school year would include all academic courses earned through the spring of the 2002–03 school year. The model including the ratio of occupational courses to academic courses also includes a squared term of that ratio to test for possible curvilinearity in the effect of CTE coursetaking.

Unlike the fixed effect approach that eliminates possible confounding effects of observed and unobserved time-invariant characteristics of students, event history models rely on observed covariates to control for differences between students. The models in the present analysis control for a host of student characteristics and experiences known to influence CTE participation and school withdrawal. These serve as useful and well-tested methods for accounting for preexisting student-level differences in the context of event history modeling (as fixed-effects event history modeling of low-proportion one-way transition events is an undeveloped area [Allison 1995]). These variables include a set of fixed (time-invariant) factors: race, poverty status, native language, sex, family structure, educational expectations, grade retention, parent’s education level, student’s employment status, reading and mathematics standardized test scores, academic disengagement, academic preparation, grade point average (GPA) in the ninth grade, school poverty level, school region, and school urbanicity. Because they are not central to the research questions posed in this analysis, and because of the volume of literature that examines their relationship to dropping out, these variables are used simply as controls; they are not reported in the main body tables or reviewed in the discussion.

Analytic Direction

As with the analysis of mathematics learning, the dropout analysis contains both a descriptive and an analytical (regression-based) element. The descriptive analysis shows the bivariate relationship between cumulative earned Carnegie units in occupational courses and rates of dropping out by semester. The analytical component examines the relationship between coursetaking and the risk of dropping out between 10th and 12th grade, controlling for student characteristics and the underlying timeline.

Findings

Semester-by-semester dropout rates are generally low (2 percent or less).

The descriptive results, presented by semester, are shown in tables 9 and 10. Table 9 shows the number of dropouts and the percentage of total sample members who were dropouts in each semester. Less than one percent of the sample dropped out during the spring of their sophomore year (2001–02), but this rose to nearly 2 percent by the following year (spring of 2002–03). The semester after modal high school completion (fall 2004) saw half of the remaining students (about 160 overall) drop out during that semester (the remaining students have censored observations).

Table 9. Dropout rates by semester

Semester	Number of dropouts	Dropout rate (weighted)
Spring 2001–02	110	0.94
Fall 2002–03	170	1.56
Spring 2002–03	200	1.90
Fall 2003–04	210	2.06
Spring 2003–04	200	2.13
Fall 2004–05	80	49.70
Total dropouts	990	8.00

N = 11,300

Exhibit reads: 106 sample members (0.94 percent of all sample members at risk during the period) dropped out during the spring of their sophomore year (2001–02).

Dropouts typically accumulate fewer academic credits than enrolled students; however, dropouts and enrolled students earn similar numbers of occupational credits.

Table 10 shows the mean number of accumulated academic and occupational courses for both continuing enrollees and dropouts. The statistical differences between enrollees and dropouts are starred. The first two panels of table 10 indicate that except for the last semester, where statistical testing was not supported, dropouts on average accumulated fewer academic credits than their enrolled peers. Only in the spring semester of the 10th grade (2001–02) did they earn fewer occupational credits—otherwise, the number of occupational credits earned does not differ between the two groups. Differences in academic coursetaking ranged between three and five credits, with the largest differences occurring in the 2003–04 school year.

Table 10. Cumulative coursetaking differences between enrolled students and dropouts by semester

Semester	Cumulative academic course credits		Cumulative occupational course credits		Percent of cumulative course credits that were occupational		Ratio of cumulative occupational to academic course credits	
	Enrolled	Dropout	Enrolled	Dropout	Enrolled	Dropout	Enrolled	Dropout
Spring 2001–02	6.3**	3.7	0.5**	0.3	7.6	7.5	10.0	12.9
Fall 2002–03	9.5**	6.3	0.8	1.0	8.1**	13.0	10.3**	18.8
Spring 2002–03	11.2**	7.5	1.1	1.1	8.8**	12.6	11.1**	17.6
Fall 2003–04	14.3**	9.3	1.5	1.4	9.6**	12.7	12.1**	16.7
Spring 2003–04	15.9**	11.3	1.8	1.9	10.2**	13.1	12.9**	17.8
Fall 2004–05	14.6†	12.9	2.1†	1.9	13.0†	12.3	13.0†	12.3

N = 11,300

The following indicates that enrolled students and dropouts were statistically significantly different at the designated *p* levels:

* $p < 0.05$

** $p < 0.01$

† Due to the reduced cell size, differences in means are not detectable with adjustments for the survey design and sampling weights.

Exhibit reads: Among students who were still enrolled in spring 2001–02, the average number of academic credits earned is 6.3. Among students who dropped out in spring 2001–02, the average number of academic credits earned is 3.7.

Although unrelated to the *total* number of occupational credits earned, dropping out is related to the *relative* mix of occupational and academic courses. The third and fourth panels of table 10 show that dropouts earned more occupational credits relative to academic courses than did continuing enrollees. Compared with enrollees, dropouts took a higher percentage of occupational courses between fall of 2002 and spring of 2004. The cumulative ratio of occupational courses to academic courses also indicates that dropouts had higher relative levels of occupational coursetaking than enrollees. However, in both of these cases, as evidenced in the first two panels of table 10, it is a lack of academic courses, and not an excess of occupational courses, that shapes the balance of courses toward CTE for dropouts.

Thus, the descriptive results suggest that occupational coursetaking has little relation to dropping out: dropouts were no more likely to take occupational courses than enrolled students. Dropouts did, however, take fewer academic courses over time than enrolled students. Dropouts began the spring semester of their sophomore year with fewer earned academic credits and fell further behind as they progressed through the next 2 years. These differences may not necessarily reflect the effect of academic and occupational courses since different types of students take different kinds of courses. Therefore table 11 presents the results from discrete-time hazard regression models predicting the odds of first dropout, controlling for a wide range of variables known to influence both coursetaking patterns and school withdrawal. Parameter estimates for the control variables included in the models are shown in appendix C, with the CTE coursetaking and timing (semester) effects presented here. The results are presented as odds ratios, with values above 1 indicating positive effects or higher odds of dropping out and values below 1 representing negative effects or lower odds of dropping out.

Table 11. Odds ratios from discrete time hazard regression models predicting dropping out of high school

	Model 1 (no student controls)	Model 2 (with controls)	Model 3 (no student controls)	Model 4 (with controls)	Model 5 (no student controls)	Model 6 (with controls)
Coursetaking						
Cumulative academic course credits	0.73**	0.81**	—	—	—	—
Cumulative occupational course credits	0.98	0.97	—	—	—	—
Percentage of cumulative course credits that were occupational	—	—	13.76**	2.19*	—	—
Ratio of cumulative occupational to academic course credits	—	—	—	—	6.69**	1.82*
Ratio of cumulative occupational to academic course credits, squared	—	—	—	—	0.70*	0.90
Semester						
Spring 2001–02 (reference)	1.00	1.00	1.00	1.00	1.00	1.00
Fall 2002–03	4.00**	2.97**	1.71**	1.81**	1.72**	1.81**
Spring 2002–03	7.55**	5.11**	2.06**	2.36**	2.08**	2.37**
Fall 2003–04	18.37**	10.22**	2.29**	2.86**	2.32**	2.88**
Spring 2003–04	27.92**	14.69**	2.26**	3.15**	2.30**	3.16**
Fall 2004–05	1,466.89**	550.35**	105.02**	85.38**	107.17**	85.89**

N = 11,300

Person-semesters at risk = 53,192

* p < 0. 05

** p < 0.01

Exhibit reads: Each additional academic credit earned is associated with a 19 percent reduction (=1 – 0.81) in the odds of dropping out of high school.

Accumulated credits in occupational courses are unrelated to the likelihood of dropping out. However, accumulated credits in academic courses are associated with a reduced likelihood of dropping out.

Models 1 and 2 of table 11 show how accumulated academic and occupational credits affect the odds of dropping out of high school.[25] Model 1 shows the relationship between coursetaking and dropping out without student controls; model 2 adds in all the control variables. In both cases, cumulative credits earned in academic courses are negatively related with the odds of dropping out. This effect is reduced if student characteristics are controlled (model 2), but still indicates that each additional academic credit, on average, is associated with a 19 percent reduction in the odds of dropping out of high school. As suggested by the descriptive analysis, these models further show that cumulative occupational credits are unrelated to the likelihood of dropping out, whether potentially confounding student characteristics are considered or not. Models 1 and 2 also show that, compared with the spring semester of their sophomore year, high school students are much more likely to drop out the longer they stay in school; once the typical graduation date is passed, remaining students are very likely to drop out.[26] This effect is substantially diminished with controls for student characteristics.

To this point, these bivariate and multivariate analyses suggest that academic courses are most important for sustaining enrollment during the last 2 years of high school. On their own, occupational courses are unrelated to dropping out of high school. However, it may be that the total number of academic or occupational courses is less important than the relative balance between them. It is to this issue that we now turn.

The cumulative percentage of courses in one's schedule that are occupational is associated with an increased likelihood of dropping out. The cumulative ratio of occupational credits to academic credits is also associated with an increased likelihood of dropping out. However, these relationships are driven by low levels of academic coursetaking among those who enroll in occupational courses.

Models 3 and 4 present results from models that operationalize coursetaking as the percentage of courses classified as occupational. Both models demonstrate that students have a higher likelihood of dropping out when occupational courses comprise a larger share of their class schedule. Specifically, after observed student characteristics are controlled, a one-point increase in the percentage of courses in a student's class schedule that are classified as occupational is associated with more than double the odds of dropping out of high school. Note, however, that the range of occupational courses as a percentage of courses is rather narrow, so that large percentage point increases are unlikely to occur. This finding may be alternatively interpreted as an increase in the percentage of academic courses being associated with a decreased likelihood of dropping out. As with models 2 and 3, the likelihood of dropping out increases over time.

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[25] In interactive analyses conducted across NCLB subgroups, sex, and BY achievement levels (findings not shown), the effects in each of the table 11 models remained consistent. Occupational coursetaking has the same effect for both poor and nonpoor students, for nonnative English speaking students and native English speaking students, for all racial-ethnic groups, for boys and girls, and for low and high achievers.

[26] The large odds ratios for fall of 2004 are common in event history models in which the base population is small and a large proportion of individuals experience the event; such estimates should be interpreted with caution.

Models 5 and 6 operationalize coursetaking as the ratio of occupational courses to academic courses. This includes a squared term for that ratio, testing whether the relationship between the ratio and dropping out is curvilinear. Model 5 contains no controls for student characteristics, while model 6 contains such controls. The detected effects in model 5 show that a higher number of occupational courses per each academic course is associated with an increased likelihood that a student may drop out, with a modest attenuation of this effect when the courseload tips heavily toward occupational courses (as evidenced by the odds ratio for the squared-cumulative ratio being less than one and significant at $p < 0.05$). Once student controls are introduced into the model (model 6), the attenuation effect disappears. The main effect, however, remains: each additional point of the ratio of occupational to academic courses is associated with an 82 percent increase in the odds of dropping out. The main effect again suggests—in combination with the knowledge that occupational coursetaking remains similar for dropouts and nondropouts (table 9)—that the effect is primarily due to low academic coursetaking. As with the other models in table 11, the likelihood of dropping out is greater in later years of high school.

The lack of the U-shaped relationship in the ratio models—detected by Plank and colleagues in their analysis of NELS:88 and the 1997 National Longitudinal Survey of Youth (Plank 2001; Plank, DeLuca, and Estacion 2008)—is a new finding, but there may be a consistent interpretation with the results reported here. Plank and colleagues find that both too few occupational courses and too many occupational courses (both relative to academic courses) leads to dropping out. However, the surveys they use follow students throughout the entire course of high school, while ELS:2002 only examines the second half of high school. If dropping out is related to too few CTE courses, as their analyses suggest, this will have likely happened before students reach the end of their sophomore year. Since ELS:2002 begins in the middle of the sophomore year, this effect is likely not detectable in the current analysis. In that respect, the current findings are not entirely incompatible with Plank and colleagues.

As was done in the achievement analysis, predicted dropout rates for different coursetaking patterns based on the full model that includes the percentage of courses classified as occupational as the main independent variable (model 4) were calculated to demonstrate the magnitude of these effects. These predicted probabilities are shown in figure 3. The bars show the predicted probability of dropping out for three sets of coursetaking patterns, assuming the student was enrolled as a sophomore in the spring of 2001–02. The first bar assumes an average course mix in every semester (15.2 percent occupational), the second bar assumes a course mix that would support classification as an occupational concentrator (19.0 percent occupational), and the third bar assumes a course mix void of occupational courses (0 percent occupational). Across the three coursetaking patterns, the probability of dropping out during the last 2 years of high school is similar, between 8 and 9 percent. Thus, while the discrete time logistic regression shows a significant relationship, differences in rates of dropping out across the three coursetaking patterns (net of the observed characteristics included the model) are substantively negligible.

Figure 3. Predicted probabilities of dropping out of high school by coursetaking patterns

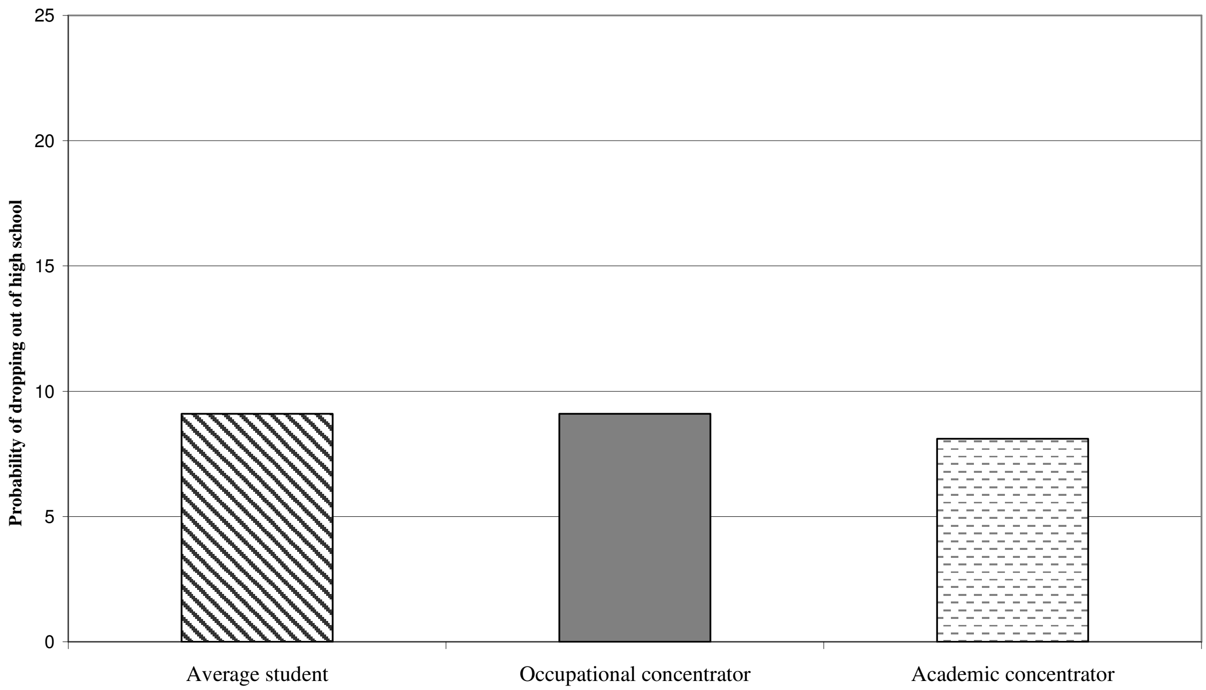

Exhibit reads: Approximately 9 percent of students classified as occupational concentrators are predicted to drop out of high school.

Failing Courses and Dropping Out. To examine the question of whether academic coursetaking is indeed driving dropout behavior, two additional issues were examined: (1) if low academic coursetaking relative to occupational coursetaking is related to high school retention and successful graduation, are specific experiences of academic failure—not passing academic courses—contributing to dropping out? (2) In addition, are occupational coursetakers who have failed academic courses more likely to drop out than students with relatively fewer failed academic courses? In other words, since the experience of failing academic courses may alter coursetaking patterns by enticing students to move away from academic coursetaking and into occupational coursetaking, are students who face such experiences dropping out at higher rates and thus revealing an indirect but negative influence of occupational coursetaking on dropout behavior?

Six models were run: the first three models replicate the full models (those with student controls) in table 11 in using cumulative academic and occupational courses taken, percentage of occupational courses taken, and ratio of occupational to academic courses taken as principal predictors, but add the cumulative numbers of failed academic courses to each model. These models show whether students with higher numbers of failed academic courses are more, less, or no more likely to drop out. The last three models repeat these models but add interaction terms between the number of failed academic courses and the occupational and academic coursetaking measures. These models indicate whether students with high occupational coursetaking (defined in the three ways used earlier) and higher values of accumulated academic course failures are more likely to drop out of high school.

Students who fail academic courses are at a higher risk of dropping out.

Table 12 presents the results from these six models. Models 1 through 3 show that the cumulative number of failed academic courses raises the odds of dropping out between 11 and 17 percent per failed course, depending on the measure of accumulated academic and occupational credits used. In other words, regardless of overall credits earned, timing of semester, or student factors, students with higher numbers of failed academic courses are more likely to dropout. The influence of regular academic and occupational coursetaking (as well as semester variables and other controls) are not substantially different from the earlier models of table 11 (see appendix C, table C-6 for all results).

The negative effect of failed academic coursetaking is attenuated if students are taking occupational courses.

Models 4 through 6 include an interaction term that measures the combined influence of failed academic courses and occupational coursetaking. When cumulative academic and occupational courses are used as the measure of coursetaking (model 10), and when the percentage of courses that are occupational is used as the measure of coursetaking (model 11), the interaction terms are not statistically significant. When the ratio of occupational to academic courses is used as the measure of coursetaking (model 12), the interaction term is statistically significant and indicates that the negative effect of failed academic coursetaking is attenuated if students are taking occupational courses. This suggests that occupational courses may serve as a mechanism to keep those in school who are struggling academically—in this case, although earned occupational credits do not overcome the influence of failing academic courses, about 63 percent of the negative influence of each failed academic course would be eliminated by each occupational credit earned.

Table 12. Odds ratios from discrete time hazard regression models predicting dropping out of high school, with effects for number of failed academic courses

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Coursetaking						
Cumulative number of failed academic courses	1.11**	1.17**	1.17**	1.12**	1.19**	1.19**
Cumulative failed academic courses X occupational course credits[1]	—	—	—	1.00	0.84	0.88**
Cumulative academic course credits	0.84**	—	—	0.84**	—	—
Cumulative occupational course credits	0.99	—	—	0.99	—	—
Percent of cumulative course credits that were occupational	—	2.26*	—	—	4.60**	—
Ratio of cumulative occupational to academic course credits	—	—	2.13*	—	—	3.52**
Ratio of cumulative occupational to academic course credits, squared	—	—	0.76	—	—	0.80
Semester						
Spring 2001–02 (reference)	1.00	1.00	1.00	1.00	1.00	1.00
Fall 2002–03	2.53**	1.68**	1.67**	2.52**	1.67**	1.68**
Spring 2002–03	3.99**	2.05**	2.04**	3.98**	2.04**	2.04**
Fall 2003–04	6.87**	2.34**	2.34**	6.87**	2.33**	2.33**
Spring 2003–04	9.39**	2.56**	2.56**	9.39**	2.54**	2.54**
Fall 2004–05	310.62**	62.05**	61.84**	311.74**	62.03**	61.88**

N = 11,300

Person-semesters at risk = 53,192

* $p < 0.05$

** $p < 0.01$

[1] Cumulative failed academic courses are interacted with cumulative occupational courses in model 4, with cumulative percent occupational courses in model 5, and with cumulative ratio of occupational to academic courses in model 6.

NOTE: All models contain student controls.

Exhibit reads: Each additional failed academic course is associated with an 11 percent increase (=1 – 1.11) in the odds of dropping out of high school.

IV. THE ROLE OF CONTEXT IN MATHEMATICHS ACHIEVEMENT AND DROPPING OUT OF HIGH SCHOOL: SCHOOL TYPE AND LOCALE

As noted earlier, recent literature has indicated that some school contexts may provide better environments for career and technical education (CTE) than others (Kimple and Willner 2008; Levesque et al. 2000). Full-time CTE schools, in particular, may offer advantages to students with an occupational coursetaking concentration by providing an encouraging peer environment and additional school resources that a comprehensive high school, providing an education to the general population, does not. In addition, students attending urban or suburban schools may reap more benefits from CTE coursetaking than students attending more remote rural schools. This section further explores these issues by addressing the question: is the relationship between CTE coursework and academic progress contingent upon the context of the school?

Sample Selection

As with prior chapters, this analysis uses Education Longitudinal Study of 2002 (ELS:2002) data on grade 10 cohort members who were part of the ELS:2002 first follow-up transcript study. Except for differences due to weighting in the analysis of dropping out (described below), the analytical samples are the same.

Independent Variables

This section focuses on two dimensions of school context: school type (full-time CTE school versus comprehensive school) and school urbanicity (rural versus urban or suburban schools). School type is identified by a binary variable taken from the National Center for Education Statistics' (NCES's) Common Core of Data and is coded "1" if the school is a full-time CTE school and "0" if it is a comprehensive high school. Missing Common Core of Data information was supplemented by school administrator surveys that provided the following information: the percentage of 12th-grade students enrolled in a vocational, technical, or business program and whether a vocational/technical program was available at that school. Schools which offered a vocational or technical program located at that school (i.e., not just at an area vocational/technical center) and that had 50 percent or more of its 12th-graders in a vocational, technical, or business program were also identified as full-time CTE schools. Approximately 1.3 percent of schools (unweighted) in the ELS sample were identified as full-time CTE schools (0.8 percent weighted). Approximately 1.4 percent of the students (unweighted) in the ELS sample attended the full-time CTE schools (1.6 percent weighted).

School urbanicity is measured by binary "dummy" variables: one each for rural schools, urban schools, and suburban schools; approximately 18.8 percent of schools (unweighted) were identified as rural schools (36.3 percent weighted).[27] Approximately 18.2 percent of students (unweighted) in the ELS sample attended rural schools (19.7 percent weighted). Since rural schools may differ from urban or suburban schools in varying ways, rural schools serve as the reference (omitted) category in all models, with urban and suburban dummy variables explicitly estimated.

All models in this section include controls for the same student background factors used in the previous chapter on dropping out. These include race, poverty status, native language, student's employment status, reading and mathematics standardized test scores, academic disengagement, academic preparation, grade point average (GPA) in the ninth grade, school poverty level, and school region. The measurement of these variables is described in appendix A.

Dependent Variables

As with previous chapters, the multilevel analysis here predicts academic progress (i.e., overall math achievement and persistence through high school) as a function of CTE coursetaking. These dependent variables are the same as the ones used in earlier chapters. However, since the purpose of this analysis is more limited, mathematics proficiency probabilities are not examined. Specific information about the outcome variables can be found in the previous chapters or in appendix A.

Analytic Direction

To understand whether school context affects math achievement or the likelihood of dropping out, methods that explicitly take into account the clustering of students within schools are required. Multilevel modeling (also called hierarchical linear modeling) is a modeling approach that takes account of this clustering and makes it possible to directly estimate the effects of school context on individual outcomes. In the current case, multilevel models can help pinpoint the influence of attendance at a full-time CTE school or a school in a rural area on math achievement and dropping out. For both outcomes, interactions between the school context variable (rural school or full-time CTE school attendance) and CTE coursetaking will indicate whether the effect of CTE coursetaking (if any) varies by school type.

For the math achievement models specifically, multilevel models are employed without taking into account the same within-person factors that the fixed-effects models employed previously. This is done because such an advanced model introduces complexities that are not necessary to answer the basic question posed: whether the effects of CTE coursetaking differ by school context. Although coefficients may be biased by unobserved heterogeneity (the situation for which the earlier fixed-effects models accounted), the statistical significance of coefficients is not (Allison 1995), and therefore the basic question can be answered.

[27] The difference in weighted versus unweighted rural school percentage is large because of oversampling of rural schools. Rural schools are typically much smaller than urban or suburban schools, and therefore, to obtain a representative sample of rural students, relatively greater proportions of rural schools must be included in the sample.

For the models of dropping out, multilevel models can be fitted that are also discrete-time event history models, and this type of model is necessary to ensure the accuracy of estimates. In this case, multilevel event history models can be estimated using discrete-outcome event history structural forms (e.g., logit or probit regression, in the same way that single-level event history models of discrete outcomes may be estimated with cross-sectional discrete-outcome forms like logit regression) (Barber et al. 2000; Guo and Zhao 2000). In the current analysis, logistic regression serves as the basis for the multilevel event-history models. While the multistage cluster design creates bias variance estimates due to the nonindependence of observations (in this case, students) clustered within a specific context (in this case, schools), multilevel models explicitly adjust for this (Raudenbush and Bryk 2002).

See appendix A for more information about multilevel models and the statistical methods used in this analysis.

Findings

Mathematics Achievement

Results for mathematics achievement are presented first. Grade 12 math score (IRT-estimated number right) is the dependent variable, with grade 10 math score a principal control (these are conditional gains models—see appendix A). Since both full-time CTE school attendance and rural school attendance are school-level characteristics, both are included in all models, along with student background effects and other school-level effects (not shown in the tables below). The effects of full-time CTE school attendance are implicitly compared in all models to all non-CTE schools (the vast majority of which are regular/comprehensive high schools), and the effects of rural school attendance are implicitly compared with nonrural school attendance (i.e., against suburban and urban schools attendance combined). Again, the occupational and academic coursetaking variables are the same as those presented in the mathematics fixed-effects analysis.

School clustering in math achievement is relatively high.

Table 13 presents model coefficients for an unconditional model (model 1) and five models containing the same specifications of occupational coursetaking used in the main analysis. The unconditional model (a model without covariates other than 10th-grade math achievement) provides information about the amount of variance in the outcome attributable to between-school differences and serves as a baseline for understanding the contributions of the independent variables used in the other models. The pattern of variance for the unconditional model indicates that approximately 16.3 percent of the variation in the grade 12 score (with the effect of grade 10 score removed) is found between schools (result not shown in table), suggesting that there is a relatively high amount of school clustering in student math scores.

Table 13. Multilevel estimates of the effect of coursetaking on the mathematics achievement number-right score

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Student-level variables						
10th-grade math number-right score	0.04**	0.80**	0.81**	0.81**	0.81**	0.81**
Cumulative occupational credits		-0.20**				
Cumulative academic credits		0.18**				
Ratio of occupational to academic credits			-5.76**			
Ratio-squared			1.64			
Percent of credits—occupational				-0.09**		
Total credits				0.11**		
Cumulative occupational math credits					0.09	
Cumulative academic math credits					0.82**	
Percent of math credits—occupational						-0.05**
Total credits						0.86**
School-level variables						
Full-time CTE school indicator		1.13	1.23	1.07	-0.47	-0.51
Urban school indicator		0.12	0.19	0.23	0.34	0.40
Suburban school indicator		0.08	0.11	0.15	0.12	0.19
Intercept	47.97**	3.98**	7.00**	4.90**	3.73**	3.72**

* p < .05
** p < .01
Source: Education Longitudinal Study of 2002 (ELS:2002), National Center for Education Statistics.

In models 2 through 6, additional variables are added: the coursetaking variables, full-time CTE attendance indicator and rural school attendance indicator, and the set of student variables (including family background, educational expectations, attitudes, and grade nine GPA and grade retention information) and other school characteristics (percentage of students participating in a free or reduced-price lunch program and regional location of school) listed in appendix A. Overall, these models explain most of the within- and between-school variation in math scores: 97 percent of the variance in math achievement scores between schools is attributable to the effects of the included variables, while 80 percent of the variance in achievement scores within schools is attributable to the effects of the included variables (these are consistent no matter the specification of the coursetaking variables, which is not surprising given that there are many more noncoursetaking variables in each of these models; they are present in every model and the coursetaking variables themselves measure similar aspects of coursetaking).

School context (attending a full-time CTE school or a rural school) has no influence on mathematics achievement.

In terms of the effects of schooling context, however, each model shows no effects for attending either a full-time CTE school (compared with other schools, mostly comprehensive high schools) or a rural school (compared with urban or suburban ones).

The effects of occupational coursetaking do not vary by full-time CTE school. However, compared with students attending a suburban school, students attending a rural school are less harmed by occupational coursetaking.

Despite these initial findings, it may still be the case that occupational coursetaking has positive effects in either a full-time CTE schooling environment or a rural schooling environment. To test this, the same models were run with interaction effects. Each occupational coursetaking variable specification was interacted with full-time CTE school attendance and suburban and urban school attendance,[28] although each interaction was added separately (i.e., the interactions for full-time CTE schools and for school locale were not added to the same model). The school locale variables compare urban and suburban school attendance each with rural school attendance (the omitted category). If statistically significant, these effects would indicate that the influence of occupational coursetaking differs by schooling context.

For the interactions between attendance at a full-time CTE school and occupational coursetaking, no coefficiencts were statistically significant; the effects of occupational coursetaking are the same whether a student attends a full-time CTE school or not. For the interactions between school locale and occupational coursetaking, the results are presented in table 14. Here the evidence in three of the five models (model 1 is the same unconditional model as in table 13) suggests that compared with students attending suburban schools, occupational coursetaking has a positive effect on math achievement for students attending rural schools (there is no statistical difference between students attending urban versus rural schools, however). The models that support this conclusion are the ones with three versions of the main occupational coursetaking measures (versus measures of mathematics content in occupationally specific courses); the size of the interaction effects in these three models differ, but they are in a consistent direction.

[28] Interaction is with the main occupational coursetaking variable for each model (i.e., in models 2–3, cumulative occupational courses; in models 4–5, ratio of occupational courses to academic courses; in models 6–7, percentage of courses that are occupational; in models 8–9, cumulative occupational math courses; in models 10–11, percentage of math courses that were occupational math.

Table 14. Multilevel estimates of the effect of coursetaking on the mathematics achievement number-right score, with interaction effects between occupational coursetaking and school locale

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Student-level variables						
Grade 10 math number-right score	0.04**	0.80**	0.81**	0.81**	0.81**	0.81**
Cumulative occupational credits		-0.12*				
Cumulative academic credits		0.18**				
Ratio of occupational to academic credits			-4.54**			
Ratio-squared			1.88			
Percent of credits—occupational				-0.06**		
Total credits				0.11**		
Cumulative occupational math credits					-0.04	
Cumulative academic math credits					0.82**	
Percent of math credits—occupational						-0.05**
Total credits						0.85**
School-level variables						
Full-time CTE school indicator		1.20	1.33	1.19	-0.62	-0.66
Urban school indicator		0.07	0.17	0.19	0.29	0.35
Suburban school indicator		0.54	0.56	0.72*	0.11	0.21
Interaction effects						
Urban school attendance x occupational coursetaking		0.07	0.95	0.02	0.45	0.02
Suburban school attendance x occupational coursetaking		-0.18*	-2.79*	-0.05**	0.11	-0.01
Intercept	47.97**	3.78**	6.78**	4.62**	3.75**	3.73**

* p < .05

** p < .01

Source: Education Longitudinal Study of 2002 (ELS:2002), National Center for Education Statistics.

Dropping Out

The multilevel dropout analysis also employs the set of semester-specific coursetaking variables used in the earlier single-level event-history analysis of dropping out. Semester-specific dropout events were the dependent variable, while independent variables (listed in the appendix) include semester dummy variables, coursetaking variables, student factors, and school characteristics. Models with cumulative failed academic courses and interactions between cumulative failed academic courses and occupational coursetaking are included. In unconditional models without these extensive controls (serving as a baseline to interpret the contributions of the controls), about 8 percent of the variance in dropout probabilities existed between schools, indicating that the multilevel approach is appropriate to account for student clustering by school (results of unconditional model not shown in table).

Cumulative occupational credits earned are associated with a lower probability of dropping out. However, the ratio or percentage of occupational credits in students' course loads is associated with a higher probability of dropping out. In addition, there is little evidence that occupational courses protect students with difficulties in academic courses from dropping out.

Table 15 presents the main findings of these models. As in chapter 3, results are presented as odds ratios, with statistically significant values lower than 1 indicating a lower likelihood of dropping out, and significant values higher than 1 indicating a higher likelihood of dropping out. Like the results from chapter 3, the multilevel models show that academic coursetaking is associated with a lower probability of dropping out; unlike the chapter 3 results, however, the effect of occupational coursetaking is statistically significant, showing a lower dropout likelihood for students earning more occupational courses (model 1). However, the results for models including the percentage of courses which are occupational or the ratio of occupational to academic courses are consistent with chapter 3 results and show that occupational courses relative to academic coursetaking loads are associated with higher probabilities of dropping out (models 3 and 5, respectively). In the ratio model (model 5), the ratio-squared term shows that sophomores have a lower probability of dropping out if their occupational course load is particularly high relative to occupational courses, suggesting support for previous indications of a U-shaped relationship between occupational coursetaking and dropping out (Plank, DeLuca, and Estacion 2008). In all of the table 15 models, the size of main effects were similar as in the nonhierarchical regression models of chapter 3.

In models adding the cumulative number of failed academic courses and an interaction effect between failed academic courses and occupational coursetaking, effects were also similar to chapter 3 results, but were more consistent. In all three cases (models 2,4, and 6 in table 15), failed academic courses were associated with higher likelihoods of dropping out, with effects somewhat larger than in earlier results. Interaction effects were mixed, with model 2 (interaction of failed academic courses and cumulative academic course credits) showing a slight increase in the likelihood of dropping out and models 4 and 6 (interacting failed academic courses with percentage and ratio occupational coursetaking measures respectively) showing a slight decrease in dropping out. The interaction results indicate that there is no strong evidence that occupational courses protect academically troubled students from dropping out.

Table 15. Odds ratios from multilevel discrete time hazard models of dropping out of high school

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Student-level variables						
Cumulative occupational credits	0.92**	0.93**				
Cumulative academic credits	0.77**	0.80**				
Percent of credits-occupational			2.30**	4.17**		
Ratio of occupational to academic credits					1.93**	3.45**
Ratio-squared					0.89**	0.70**
Cumulative failed academic credits		1.16**		1.28**		1.28**
Interaction of failed academic credits and occupational course measure[1]		1.01**		0.98**		0.98**
School-level variables						
Full-time CTE school indicator	0.33	0.31	0.48	0.43	0.46	0.42
Urban school indicator	1.39	1.28	1.32	1.18	1.33	1.20
Suburban school indicator	0.92	0.87	1.01	0.92	1.01	0.92

* p < .05

** p < .01

Note: Person-years = 53,278

[1] Cumulative failed academic courses interacted with occupational course measure specific to each model: in model 2, cumulative occupational courses; in model 4, the percentage of all courses that were occupational; and in model 6, the ratio of occupational to academic courses.

Source: Education Longitudinal Study of 2002 (ELS:2002), National Center for Education Statistics.

The main effects for the different occupational coursetaking measures are stronger in some models containing the measure of the cumulative number of failed academic courses and its interaction with the occupational coursetaking measure (models 2, 4, and 6). Both the percentage of courses that are occupational and the ratio of occupational courses to academic courses show probabilities of dropping out that are nearly twice as high as in models that do not control for failed academic courses. Regardless, both models continue to indicate that dropping out of high school is more likely if occupational courses comprise a larger proportion of credits of credits earned.

Attendance at a full-time CTE school or a rural school has no relationship with dropping out.

The last two rows of table 15 show the school-level effects for attendance at a full-time CTE school or a rural school. As with the analysis of mathematics coursetaking, there is no statistically significant association between these school context variables and dropping out.

The effects of occupational coursetaking on dropping out show no consistent differences across school contexts.

Is the effect of occupational coursetaking on dropping out different if a student attends a full-time CTE school or a rural school? To answer this question, interactions were added to the models of table 14 and the results are shown in tables 16 and 17. In table 16, interactions between full-time CTE attendance and occupational coursetaking measures are presented. In table 17, interactions between suburban and urban school attendance and occupational coursetaking measures are presented (with rural schools as the reference category). The main effects for coursetaking and school context are similar to the results already shown in table 15, so the discussion here focuses only on the interaction effects. These are shown in the last row of both table 16 and 17.

There are no consistent differences in the effect of occupational coursetaking by full-time CTE or school locale. Positive, negative, and nonsignificant interaction terms are observed in both table 16 and table 17, depending on the occupational coursetaking measure used and whether the effects of failed academic courses are controlled. For example, occupational coursetaking among students in full-time CTE schools appears to increase the probability of dropping out when occupational courses are measured separately from academic courses (models 1 and 2, table 16), but models including failed academic courses and measuring occupational coursetaking as a percentage or ratio of courses (models 4 and 6, table 16) suggest that occupational coursetaking in full-time CTE schools lowers the likelihood of dropping out.

Table 16. Odds ratios of interactions between full-time CTE school attendance and occupational coursetaking

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Student-level variables						
Cumulative occupational credits	0.91**	0.93**				
Cumulative academic credits	0.77**	0.80**				
Percent of credits-occupational			2.26**	4.19**		
Ratio of occupational to academic credits					1.93**	3.45**
Ratio-squared					0.89**	0.70**
Cumulative failed academic credits		1.16**		1.28**		1.28**
Interaction of failed academic credits and occupational course measure[1]		1.01**		0.98**		0.98**
School-level variables						
Full-time CTE school indicator	0.25	0.26	0.42	0.46	0.45	0.46
Urban school indicator	1.39	1.28	1.32	1.18	1.33	1.19
Suburban school indicator	0.92	0.87	1.01	0.91	1.01	0.92
Interaction effects						
Full-time CTE school attendance x occupational coursetaking[2]	1.11**	1.07**	1.77**	0.72*	1.06	0.75**

* p < .05; ** p < .01

Note: Person-years = 53,278

[1] Cumulative failed academic courses interacted with occupational course measure specific to each model: in model 2, cumulative occupational courses; in model 4, the percentage of all courses that were occupational; and in model 6, the ratio of occupational to academic courses.

[2] Full-time CTE school attendance interacted with occupational course measure specific to each model: in models 1 and 2, cumulative occupational courses; in models 3 and 4, percentage of all courses that were occupational; and in models 5 and 6, the ratio of occupational to academic courses.

Source: Education Longitudinal Study of 2002 (ELS:2002), National Center for Education Statistics.

In terms of rural school attendance, results from table 17 show additional mixed results. Both positive and negative differences in occupational coursetaking effects appear, depending on whether students in rural schools are being compared with students in urban or suburban schools. In models 1 and 2, rural students with more occupational earned credits appear to have lower dropout likelihoods than urban students, but higher likelihoods than suburban students. In contrast, models 3 through 6 show the opposite. Absent privileging one model specification over another, it is unclear whether and what type of influence occupational coursetaking has among students attending rural schools.

Table 17. Odds ratios of interactions between urban and suburban school attendance and occupational coursetaking

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Student-level variables						
Cumulative occupational credits	0.93**	0.94**				
Cumulative academic credits	0.77**	0.80**				
Percent of credits-occupational			2.03**	4.08**		
Ratio of occupational to academic credits					1.98**	3.51**
Ratio-squared					0.84**	0.68**
Cumulative failed academic credits		1.16**		1.28**		1.28**
Interaction of failed academic credits and occupational course measure[1]		1.01**		0.98**		0.98**
School-level variables						
Full-time CTE school indicator	0.33	0.31	0.47	0.42	0.45	0.41
Urban school indicator	1.38	1.27	1.36	1.22	1.37	1.23
Suburban school indicator	0.96	0.90	0.95	0.89	0.97	0.90
Interaction effects						
Urban school attendance x occupational coursetaking[2]	1.01*	1.01**	0.64**	0.72**	0.73**	0.78**
Suburban school attendance x occupational coursetaking[2]	0.97**	0.97**	1.58**	1.19**	1.22**	1.41**

* p < .05; ** p < .01

Note: Person-years = 53,278

[1] Cumulative failed academic courses interacted with occupational course measure specific to each model: in model 2, cumulative occupational courses; in model 4, the percentage of all courses that were occupational; and in model 6, the ratio of occupational to academic courses.

[2] Urban and suburban school attendance interacted with occupational course measure specific to each model: in models 1 and 2, cumulative occupational courses; in models 3 and 4, percent of all courses that were occupational; and in models 5 and 6, the ratio of occupational to academic courses.

Source: Education Longitudinal Study of 2002 (ELS:2002), National Center for Education Statistics.

Summary

Results showed that variation in math achievement and high school persistence was clustered within schools, supporting the use of multilevel models that could more precisely identify the effects of school context. Results for occupational coursetaking effects were nevertheless largely consistent with nonmultilevel estimates presented in chapter 3, although there was more consistent evidence for occupational coursetaking limiting mathematics achievement gain and increasing dropout likelihoods. In models using a variety of measures of occupational coursetaking and controlling for student factors and school characteristics, being in a full-time CTE school or a rural school was unrelated with achievement or dropping out. However, occupational coursetaking was less harmful for students attending rural schools compared with students attending urban schools, though there were no differences in occupational coursetaking effects on math achievement growth across full-time CTE versus other school contexts. There were no consistent differences in dropout outcomes when occupational coursetaking was considered in the context of attending and full-time CTE school or a rural school. These results suggest that the role of occupational coursetaking in encouraging persistence through high school may be related to the school's locale, but that further research focused on contextual differences would be necessary to determine the precise relationships involved.

V. CONCLUSION

As stated at the outset of this report, a key goal of career and technical education (CTE) (as stated in the reauthorization of the Perkins legislation) is to enhance both the academic and occupational preparedness of youth leaving high school. This report focuses specifically on the academic goals of CTE using a nationally representative sample of youth who finished high school following the passage of Perkins III. On average, the analysis shows that occupational courses taken during the last 2 years of high school do not impede learning gains in mathematics, but when taken in place of academic courses may limit the acquisition of advanced skills and concepts. These relationships, however, are rather *modest*. Additionally, the total number of occupational courses is unrelated with dropping out of high school. However, the odds of dropping out are higher when occupational courses comprise a large share of students' courses. In accord with past research, academic courses bear heavily on academic progress: taking more academic courses is associated with an increase in mathematics learning and a reduction in the likelihood of dropping out of high school. The specifics of these findings are discussed in turn.

Mathematics Gains

This analysis used an aggregate test score to assess overall gains in mathematics along with five proficiency probability scores to assess gains in specific mathematics skills and concepts. Corroborating past research (Rasinksi and Pedlow 1998), this analysis finds that the number of occupational courses taken during the last 2 years of high school neither enhances nor inhibits overall mathematics learning gains. In a new finding, we also show that attendance at a full-time CTE high school, and occupational coursetaking within full-time CTE schools or rural schools (where there might be expectations for occupational coursetaking influence), are unrelated to mathematics gains.

However, if occupational courses are taken at the expense of academic courses, overall learning gains are somewhat limited. For the specific skills and concepts learned, occupational coursetaking is largely unrelated to the acquisition of basic and intermediate mathematics skills. However, the development of advanced skills such as solving multistep word problems is impeded when occupational courses comprise a larger share of students' course schedules. *These effects, however, are rather modest*: the gains that accrue from taking all academic courses in the last 2 years of high school are comparable to the gains that accrue from taking a mix of academic and occupational courses. While this may at first seem counterintuitive, recall that the Education Longitudinal Study of 2002 (ELS:2002) is an observational data set; none of the students were randomly assigned to different coursetaking sequences. Most of the achievement differences between students who take a large number of occupational courses and students who take few or no occupational courses are largely due to *preexisting differences* between students before they enter the last 2 of years of high school, not the courses taken during this time. It is not that coursework is inconsequential for learning, but that in a nationally representative sample, those who are high achievers tend to be concentrated in academic courses, while low achievers tend to be concentrated in CTE courses. With these selection processes operating long before students reach the end of high school, the effect that can be *solely* attributed to coursework in the 11th and

12th grade is small. Future research using experimental design methods will be needed to clarify the magnitude of the relationships detected here.

Concerns that the academic performance of economically disadvantaged students, nonnative English speaking students, and racial and ethnic minorities—three of the four subgroups monitored by the No Child Left Behind legislation—will be disadvantaged by occupational courses, at least in terms of learning in mathematics, are not supported in ELS:2002. Occupational courses have similar effects on math achievement for both poor and nonpoor students as well as nonnative English speakers and native English speakers. Additionally, some evidence indicates that CTE in some cases may enhance the performance of racial and ethnic minorities. Black and Asian students benefit more from occupational courses than do White students. Occupational courses improve the development of basic and intermediate skills more so for Black students than for White students and the development of intermediate and advanced skills more so for Asian students than for White students.

Because many of the skills and concepts assessed in standardized mathematics achievement tests are rarely those most emphasized in occupational courses, the results present only a partial view of the learning that takes place in the CTE curriculum. However, a subset of occupational courses incorporates quantitative skills, problem solving, and logic (OE/STEM courses). By and large, these courses are unrelated to math achievement. However, there is some evidence that that may inhibit learning at level 4, one of the more advanced levels, if they replace traditional academic math courses. This relationship is modest.

Dropping Out

To assess the relationship between CTE and dropping out, semester-by-semester coursetaking patterns and enrollment/dropout histories were compiled. Both descriptive and multivariate analyses based on these histories present a consistent story: the total number of occupational courses earned has no independent influence on the likelihood a student drops out of high school. In addition, attendance at a full-time CTE high school does not affect dropping out (nor is there a consistent finding with regard to whether occupational coursetaking influences dropping out among those attending full-time CTE schools or those attending rural schools, in which contexts occupational coursetaking may also be hypothesized to have an influence). These results challenge the assumption that occupationally relevant coursework will engender interest in schooling and, thus, serve as a means to sustain enrollment; neither will it necessarily lead to disengagement from school. However, occupational courses may disrupt enrollment if they are taken at the expense of academic courses: course schedules that include a large number of occupational courses relative to academic courses are associated with increased odds of dropping out. This complements previous work by Plank and others who find the odds of dropping out are lowest for students who take a relative balance of occupational to academic courses. Since the analyses reported here focus on occupational coursetaking as a whole, they do not necessarily indicate that specific types of occupational coursetaking or programs will have no influence (positive or negative) on dropping out, as some detailed prior research has concluded (e.g., Ainsworth and Roscigno 2005; Arum 1998). Rather, it supports the conclusion that CTE courses do not serve to prevent dropping out, and when taken alongside only a small number of academic courses, may increase the risk of dropping out.

Although the findings reported do not demonstrate the efficacy of CTE, as stated in the Perkins legislation, in meeting “challenging academic content standards and student academic achievement standards,” there is no evidence that occupational courses themselves compromise academic progress. Poorer outcomes for students taking occupational courses are not caused by the occupational courses themselves, but to the types of students that are selected into occupational courses and the dearth of academic courses in their schedules. However, the findings reported here only reflect the effect of coursetaking. In addition to formal coursework, CTE encompasses a wide range of activities, such as cooperative education, structured work force experience, job shadowing, and career mentorship. Although some of these activities may be used by students who attend a full-time CTE high school (and no relationship between such attendance and dropping out was observed), the findings cannot be extrapolated to this range of initiatives undertaken to enhance occupational preparation during the high school years. Additionally, the analysis is based on an aggregate course classification scheme, not on the type of instruction used or the use of hands-on applications. As such, the goal of integrating academic and occupational content as it occurs within individual classes cannot be assessed here.

Despite the strengths of this study—for example, the longitudinal design, course information from administrative records, and assessments scaled to different proficiency levels—ELS:2002, like other National Center for Educational Statistics data sets, is observational. As such, students were not randomly assigned to schools, classrooms, or course sequences, limiting the ability to establish a causal link between CTE courses and academic progress. The analysis of mathematics learning gains employed fixed-effects regression procedures, which eliminate the potentially confounding effects of any individual or period-specific time-invariant characteristics, thus providing stronger causal evidence than the regression-based covariate adjustment methods used in past research with observational data. Readers should note, however, that estimates from fixed-effects models are only unbiased if no time-varying characteristics influence the relationship between the key predictor and the outcome. To guard against this possibility, time-varying measures of students’ time use, orientations toward schooling, self-efficacy in math, parental involvement, and grade retention as well as the survey year, are included in all models. While this tempers concerns about the influence of unobserved time-varying characteristics threatening the estimates, it does not entirely rule out the possibility of biased estimates.

The analysis of dropping out used event history methods whereby preexisting differences between students were accounted for by controlling for observed socioeconomic and academic characteristics of students before they entered the second half of high school. While the relationship between the relative coursetaking mix and dropping out was robust when these controls were applied, unmeasured characteristics may still influence selection into CTE coursetaking and influence dropping out. As such, a direct causal relationship cannot be established here.

In closing, as the economy becomes increasingly reliant on strong quantitative and analytical skills, policy makers must grapple with the best ways to prepare all youth for the challenges of postsecondary life—be it further education, employment, or both. This study shows that CTE as a policy designed to improve academic preparation is not entirely successful when using learning in mathematics and dropout prevention as the evaluation criteria. Students make the largest gains in mathematics and are least likely to drop out when they enroll in academic courses. Any detected negative effect of CTE is substantively negligible, and is mostly driven by preexisting differences between students who follow a CTE-focused curriculum and students who follow an academic-focused curriculum.

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Appendix A
Technical Description of Data and Methods

Education Longitudinal Study of 2002 (ELS:2002) Base-Year and First Follow-up Study Design and Content

Base-year (BY) Study Design. Seven study components comprised the BY design: assessments of students (achievement tests in mathematics and reading); a survey of students; surveys of parents, teachers, school administrators, and librarians; and a facilities checklist (completed by survey administrators, based on their observations at the school). The student assessments measured achievement in mathematics and reading. Mathematics achievement was reassessed in the first follow-up, so that achievement gain over the last 2 years of high school can be measured and related to coursetaking. The student questionnaire gathered information about the student's background, school experiences and activities, plans and goals for the future, employment and out-of-school experiences, language background, and motivation toward learning.

One parent of each participating sophomore was asked to respond to a parent survey. The parent questionnaire was designed to gauge parental aspirations for the child, home background and the home education support system, the child's educational history prior to 10th grade, and parental interactions with and opinions about the student's school. For each student enrolled in English or mathematics, a teacher was also selected to participate in a teacher survey. Teachers typically (but not always) reported on multiple ELS:2002 sophomores. The teacher questionnaire collected the teacher's evaluation of the student and provided information about the teacher's background and activities. The head librarian or media center director at each school was asked to complete a library media center questionnaire, which inquired into the school's library media center facility, its staffing, its technological resources, collection and expenditures, and scheduling and transactions. Finally, the facilities checklist was a brief observational form completed for each school. The form collected information about the condition of school buildings and facilities.

First Follow-up (F1) Study Design. In the F1 interview, BY schools were surveyed by means of an administrator questionnaire. BY students were surveyed whether in the BY school, in a new school, or out of school. A mathematics assessment was administered to F1 students in the original (BY) sample of schools. Those who had dropped out were administered a special questionnaire about their previous experiences in school, when and why they dropped out, and current work and family activities. Further details on the instrumentation, sample design, data collection results, data processing, weighting and imputation, and data files available for analysis may be found in the *Education Longitudinal Study of 2002/2004: Base-Year to First Follow-up Data File Documentation* (Ingels et al. 2005).

Transcript Study Design. Transcripts were collected from sample members in late 2004 and early 2005, about 6 months to 1 year after most students had graduated from high school. Collecting the transcripts in the 2004–05 academic year allowed for more complete high school records. Transcripts were collected from the school that the students were originally sampled from in the BY (which was the only school for most sample members) and from their last school of attendance if it was learned during the F1 student data collection that they had transferred.

The ELS:2002 high school transcript data collection sought key pieces of information about coursetaking from the student's official high school record—including courses taken while attending secondary school, information on credits earned, year and term courses were taken, and final grades. When available, other information was collected, including dates enrolled, reason for leaving school, and standardized test scores. This information, in conjunction with the F2 interview, is used to identify the timing of dropping out for the analysis in this report. Once collected, the data were transcribed and linked back with the student's questionnaire and assessment data. Because of the size and complexity of the file, and because of reporting variation by school, additional variables were constructed from the raw transcript file. Further details on the instrumentation, sample design, data collection results, data processing, weighting and imputation, and data files available for analysis may be found in the *Education Longitudinal Study of 2002: First Follow-up Transcript Component Data File Documentation* (Bozick et al. 2006).

Base-Year to First Follow-up Mathematics Tests

Test Design and Format. Test specifications for the BY and F1 assessments were adapted from frameworks used for NELS:88. The framework had two levels: content areas and cognitive processes. Content areas included arithmetic, algebra, geometry, data/probability, and advanced topics. Cognitive process areas included skill/knowledge, understanding/ comprehension, and problem solving. The test questions were selected from previous assessments: the National Education Longitudinal Study of 1988 (NELS:88), the National Assessment of Educational Progress (NAEP), and the Program for International Student Assessment (PISA). Most, but not all BY items were multiple choice; about 10 percent were open-ended. In the F1 assessment, all items were multiple choice. Both BY and F1 items were field tested in 2001, and 12th-grade items were field tested again in 2003. Items were selected or modified based on field test results. Final forms were assembled based on psychometric characteristics and coverage of framework categories.

The ELS:2002 assessments were designed to maximize the accuracy of measurement that could be achieved in a limited amount of testing time while minimizing floor and ceiling effects, by matching sets of test questions to initial estimates of students' achievement. In the BY, this was accomplished by means of a two-stage test. All students received a short multiple-choice routing test, scored immediately by survey administrators who then assigned each student to a low, middle, or high difficulty second-stage form, depending on the student's number of correct answers in the routing test. In the F1 administration, students were assigned to an appropriate test form based on their performance in the BY. Cut points for assignment to the F1 low, middle, and high forms were calculated by pooling information from the field tests for 10th and 12th grades in 2001, the 12th-grade field test in 2003, and the BY national sample. Item and ability parameters were estimated on a common scale. Growth trajectories for longitudinal participants in the 2001 and 2003 field tests were calculated, and the resulting regression parameters were applied to the 10th-grade national sample. Test forms were designed to match the projected achievement levels of the lowest and highest 25 percent, and the middle 50 percent, of the BY sample 2 years later. Each test form contained 32 multiple-choice items.

Item Response Theory Scoring Procedures. The scores used to describe students' performance on the direct cognitive assessment are broad-based measures that report performance as a whole. The scores are based on Item Response Theory (IRT), which uses patterns of correct, incorrect, and omitted answers to obtain ability estimates that are comparable across different test forms.[29] In estimating a student's ability, IRT also accounts for each test question's difficulty, discriminating ability, and a guessing factor.

IRT has several advantages over raw number-right scoring. By using the overall pattern of right and wrong responses to estimate ability, IRT can compensate for the possibility of a low-ability student guessing several difficult items correctly. If answers on several easy items are wrong, a correct difficult item is assumed, in effect, to have been guessed. Omitted items are also less likely to cause distortion of scores, as long as enough items have been answered right and wrong to establish a consistent pattern. Unlike raw number-right scoring, which necessarily treats omitted items as if they had been answered incorrectly, IRT procedures use the pattern of responses to estimate the probability of correct responses for all test questions. Finally, IRT scoring makes it possible to compare scores obtained from test forms of different difficulty. The common items present in overlapping forms and in overlapping administrations (10th grade and 12th grade) allow test scores to be placed on the same scale.

In the ELS:2002 F1 survey, IRT procedures were used to estimate longitudinal gains in achievement over time by using common items present in both the 10th- and 12th-grade forms. Items were pooled from both the 10th- and 12th-grade administrations and anchored to the IRT scale of the NELS:88 survey of 1988–92. Item parameters were fixed at NELS:88 values for the items that had been taken from the NELS:88 test battery and to BY values for non-NELS:88 items. In each case, the fit of the follow-up item response data to the fixed parameters was evaluated, and parameters for common items whose current performance did not fit previous patterns were reestimated, along with non-NELS:88 items new to the follow-up tests.

Score Descriptions. Two different types of IRT scores are used in this report to describe students' performance on the mathematics assessment. NELS:88-equated *IRT number-right scores* measure students' performance on the whole item pool. NELS:88-equated *proficiency probabilities* estimate the probability that a given student would have demonstrated proficiency for each of the five mathematics levels defined for the NELS:88 survey in 1992.[30]

ELS:2002-NELS:88 Equating. Equating the ELS:2002 scale scores to the NELS:88 scale scores was completed through common-item or *anchor equating*. The ELS:2002 and NELS:88 mathematics tests shared 44 mathematics items. These common items provided the link that made it possible to obtain ELS:2002 student ability estimates on the NELS:88 ability scale. (The ELS:2002 data for 12 additional mathematics items did not fit the NELS:88 IRT

[29] For an account of Item Response Theory, see Embretson and Reise (2000) or Hambleton, Swaminathan, and Rogers (1991).
[30] For further information on the NELS:88 proficiency levels, see Rock and Pollack (1995), *Psychometric Report for the NELS:88 Base Year Through Second Follow-up* (NCES 95-382).

parameters, so these items were not treated as common items for equating.) Parameters for the common items were fixed at their NELS:88 values, resulting in ability estimates consistent with the NELS:88 metric.

Number-right Scores. The NELS:88-equated IRT number-right scores for mathematics are estimates of the number of items students would have answered correctly had they taken the NELS:88 exam and responded to all items in the mathematics items pool. The NELS:88 item pool contained 81 mathematics items in all test forms administered in grades 8, 10, and 12. These scores are not integers because they are sums of probabilities, not counts of right and wrong answers.

Proficiency Probability Scores. The criterion-referenced NELS:88-equated proficiency probability scores are based on clusters of items that mark different levels on the mathematics scale. Clusters of four items were identified in the NELS:88 tests that marked five hierarchical levels in mathematics:

1. simple arithmetical operations on whole numbers, such as simple arithmetic expressions involving multiplication or division of integers;
2. simple operations with decimals, fractions, powers, and roots, such as comparing expressions, given information about exponents;
3. simple problem solving, requiring the understanding of low-level mathematical concepts, such as simplifying an algebraic expression or comparing the length of line segments illustrated in a diagram;
4. understanding of intermediate-level mathematical concepts and/or multistep solutions to word problems such as drawing an inference based on an algebraic expression or inequality; and
5. complex multistep word problems and/or advanced mathematics material such as a two-step problem requiring evaluation of functions.

In this report, level 1 is considered basic skills, levels 2 and 3 are considered intermediate skills, and levels 4 and 5 are considered advanced skills.

The proficiency levels are hierarchical in the sense that mastery of a higher level typically implies proficiency at lower levels. The NELS:88-equated proficiency probabilities in ELS:2002 were computed using IRT item parameters calibrated in NELS:88. Each proficiency probability represents the probability that a student would pass a given proficiency level defined as above in the NELS:88 sample. The mean of a proficiency probability score aggregated over a subgroup of students is analogous to an estimate of the percentage of students in the subgroup who have displayed mastery of the particular skill. The proficiency probability scores are particularly useful as measures of gain because they can be used to relate specific treatments (such as selected coursework) to changes that occur at different points along the score scale. For example, two groups may have similar gains in total scale score points, but for one group, gain may take place at an upper skill level, and for another, at a lower skill level. One would expect to see a relationship between gains in probability of proficiency at a particular level and curriculum exposure, such as taking mathematics courses relevant to the skills being mastered.

Bias Analysis. A bias analysis was conducted to assess the generalizability of the final analytic sample for the mathematics achievement analysis (N = 7,160) and the final analytic sample for the dropout analysis (N = 11,300) by comparing the composition of these samples with the target population of sophomores who were enrolled in the spring of 2002 (N = 16,170). Table A-1 shows the weighted distributions of select student characteristics used in this study measured in the BY interview.

Table A-1. Bias analysis: All members of sophomore cohort, mathematics achievement analytic sample, and dropout analytic sample, by student characteristics

	Spring 2002 sophomore cohort sample	Mathematics achievement analytic sample	Dropout analytic sample
NCLB subgroups in 10th grade			
Economic disadvantage	15.0	12.6	15.2
Limited English proficiency	14.0	12.2	14.0
Race/ethnicity			
Black	14.4	12.6	14.3
White	60.3	65.1	60.4
American Indian	1.0	0.1	1.0
Asian	4.2	3.9	4.0
Hispanic	15.9	13.7	16.1
More than one race	4.3	3.8	4.3
Time use and orientations toward school in 10th grade			
Math homework	83.2	84.0	82.8
Extracurricular activities	60.8	65.5	60.5
Employment	59.7	58.9	59.4
Importance of education	82.7	84.9	83.0
Expects college degree	79.4	82.6	79.0
10th-grade mathematics achievement number right	44.4	46.2	44.2
Level 1	0.92	0.93	0.92
Level 2	0.67	0.72	0.67
Level 3	0.46	0.52	0.46
Level 4	0.20	0.24	0.20
Level 5	0.01	0.01	0.01
N	16,170	7,160	11,300

Although the differences are not large, the mathematics achievement analytic sample has slightly more socioeconomic and academic resources than the spring 2002 sophomore cohort. The mathematics achievement analytic sample has fewer students in poverty and fewer racial-ethnic minorities than the overall sophomore cohort. Additionally, the mathematics achievement analytic sample participates in extracurricular activities at higher rates and has slightly higher levels of mathematics achievement in the 10th grade than the overall sophomore cohort. This is not surprising as the mathematics achievement analytic sample excludes students who had transferred, students who had dropped out, students who were absent on the day of the test administration, and students with incomplete transcripts, all of whom typically do less well in school than their peers. Therefore, the analytic sample used in the mathematics achievement analysis does not entirely approximate the composition of the full sophomore panel. Despite these differences, it is imperative to have complete transcript information and to have mathematics achievement test scores in both the BY and the F1 to accurately answer the research questions posed in this report. A consequence of using the analytic sample is that the findings may not generalize to all students, particularly those who are economically disadvantaged, non-White, and low achieving. Readers should keep this caveat in mind when interpreting the results in the mathematics achievement analysis. By and large, the distributions for the dropout analytic sample approximate the distributions for the 2002 spring sophomore cohort.

Statistical Methods: Mathematics Achievement Analysis

Model Selection. To estimate the effect of coursetaking on achievement gains, three potential models were considered: Ordinary Least Squares (OLS) regression models, conditional change regression models, and fixed-effects regression models. Each are briefly described below.

Ordinary Least Squares Regression Models

The general form of the OLS model is

$$y_t = \alpha + \beta_1 OCC_t + \beta_2 ACAD_t + \varepsilon_t \qquad \text{(equation 1)}$$

where y is the mathematics achievement score for students at the end of 12th grade (t = F1 interview); OCC is the number of occupational credits earned by the end of 12th grade; ACAD is the number of academic credits earned by the end of 12th grade; α, β_1, and β_2 are parameters to be estimated, and ε is random error. A key assumption of the OLS model is that the error term, ε, is uncorrelated with the independent variables OCC and ACAD. Given that students are typically not randomly assigned to courses, it is very likely that unmeasured characteristics correlate with OCC and ACAD not included this model. If so, the assumption that ε is uncorrelated with OCC and ACAD is violated and the corresponding parameter estimates will be biased.

Conditional Change Regression Models

This model takes advantage of the panel quality of the ELS:2002 data where mathematics achievement is measured at two points in time. The general form of the model is

$$y_t = \alpha + \beta_1 OCC_{t \ldots t-1} + \beta_2 ACAD_{t \ldots t-1} + \beta_3 y_{t-1} + \delta_1 \mathbf{X}_{t-1} + \varepsilon_t \qquad \text{(equation 2)}$$

where y_t is the mathematics achievement score for students at the end of 12th grade (F1 interview) and y_{t-1} is the mathematics achievement score for students at the end of 10th grade (BY interview); OCC is the number of occupational credits earned during the 11th and 12th grades; ACAD is the number of academic credits earned during the 11th and 12th grades; **X** is a vector of control variables measured at the end of the 10th grade; α, β_1, β_2, β_3, and δ_1 are parameters to be estimated, and ε is random error. For the parameters associated with the coursetaking measures to be unbiased, the BY math achievement score (y_{t-1}) and the control variables (**X**) must capture everything up to the end of the 10th grade that is related to OCC and

ACAD. If this condition holds, then any variation in OCC and ACAD between 10th and 12th grade is exogenous and the parameter estimates associated with OCC and ACAD represent the true effect of coursetaking on achievement.

Fixed-effects Regression Models

In conventional OLS and conditional change regression models, control variables can be used to remove the effect of potentially confounding observed variables (as is done in equation 2). However, if there are unobserved characteristics that are correlated with the key predictor variables and the outcome net of the observed controls, the estimated effects of the key predictor variables will be biased. Unlike OLS and conditional change regression models, fixed-effects regression absorbs both observed and unobserved potentially confounding time-invariant characteristics, and therefore provides the best linear unbiased estimate of the key predictor variables. In a fixed-effects model, these time-invariant characteristics are measured by a fixed constant α_i that differs for each individual *i*. The form of the model used in this analysis is

$$y_{it} = \beta_1 OCC_{it} + \beta_2 ACAD_{it} + \delta_1 \mathbf{X}_{it} + \gamma_1 YEAR_{it} + \alpha_i + \varepsilon_{it} \qquad \text{(equation 3)}$$

where *y* is the mathematics achievement score for individual *i* at time *t*, *t* = BY interview, F1 interview; OCC is the number of occupational credits for individual *i* at time *t*; ACAD is the number of academic credits for individual *i* at time *t*; **X** is a vector of time-varying control variables where time use, orientations toward schooling, self-efficacy in math, parental involvement, and grade retention are measured for individual *i* at time *t*; YEAR is a binary indictor of the survey administration (0 = BY interview; 1 = F1 interview); α_i is a fixed constant that differs for each individual *i*; β_1, β_2, δ_1,and $\gamma_1$are parameters to be estimated; and ε is random error for individual *i* at time *t*. To estimate the model, each individual's mathematics achievement score at each time point can be expressed as a deviation from their mean score at each time point:

$$y_{it} - \overline{y_i} = \beta_1\left(OCC_{it} - \overline{OCC_i}\right) + \beta_2\left(ACAD_{it} - \overline{ACAD_i}\right) + \delta_1\left(\mathbf{X}_{it} - \overline{\mathbf{X}_i}\right) + \gamma_1\left(YEAR_{it} - \overline{YEAR_i}\right) + \left(\varepsilon_{it} - \overline{\varepsilon_i}\right).$$

In this differencing estimator, all time-invariant characteristics (α_i) are eliminated because the difference will always equal zero thus alleviating the problem of selection bias. Observed time-varying factors contained in **X** remove the confounding effects of time use, orientations toward schooling, self-efficacy in math, parental involvement, and grade retention observed in the data. Any natural growth in mathematics learning overtime is controlled for by the time-varying measure of survey year (YEAR). The resulting estimates of coursetaking (β_1 and β_2) will be unbiased as long as there are no unobserved time-varying characteristics influencing the relationship between coursetaking and mathematics achievement.

Model Comparisons

All three models were examined to assess the patterning of the findings when different assumptions are applied. Specifically, equations 1–3 were estimated with OCC and ACAD as the key predictor variables for each of the six math achievement outcomes. Next, OCC and ACAD were replaced with the measure of the percentage of courses that were occupational and the estimation was repeated. The findings are shown in table A-2. For clarity and succinctness, the parameter estimates for the control variables are not shown.

Table A-2. Model selection estimates for the regression of math achievement on coursetaking

	Ordinary least squares regression coefficients	Conditional change regression coefficients	Fixed-effects regression coefficients
Academic courses number right	1.638**	0.548**	0.345**
Level 1	0.009**	0.004**	-0.003**
Level 2	0.034**	0.010**	-0.002**
Level 3	0.046**	0.018**	0.004**
Level 4	0.041**	0.018**	0.015**
Level 5	0.008**	0.007**	0.009**
Occupational courses number right	-0.180	-0.094	-0.089**
Level 1	0.003**	0.002**	-0.001**
Level 2	0.002	0.002	0.001**
Level 3	-0.004	-0.002	-0.000**
Level 4	-0.011**	-0.006**	-0.004**
Level 5	-0.002**	-0.001	-0.001**
Percent occupational courses number right	-0.366**	-0.054**	-0.054**
Level 1	-0.001**	-0.000	0.001**
Level 2	-0.007**	-0.001**	0.001**
Level 3	-0.010**	-0.002**	-0.000**
Level 4	-0.010**	-0.002**	-0.003**
Level 5	-0.002**	-0.001**	-0.001**

N = 7,160
* $p < 0.05$
** $p < 0.01$

From left to right, the test of the effect of coursetaking on math achievement becomes more stringent as the models remove the effects of potentially confounding factors. If the OLS model was unbiased, then the results would be similar when comparing it with the other two models. This is not the case. The magnitude of the estimates for academic and occupational courses is generally smaller in the conditional change models than in the OLS models, and smaller still in the fixed-effects models. The significant positive effect of academic courses for level 1 detected in the OLS model is significant and negative when tested in the fixed-effects framework and the significant positive effect of academic courses for level 2 detected in the OLS model loses significance when tested in the fixed-effects framework. Similarly, the significant positive effect of occupational courses at level 2 and the significant negative effect of occupational courses at level 4 are both found insignificant in the fixed-effects model.

Similar patterns hold when considering the percentage of courses that are occupational as the main predictor. The OLS models find a significant negative effect on all six outcomes, while the fixed-effects models find a significant negative effect on only three outcomes (number right, level 4, and level 5) and a positive effect on one outcome (level 1). As an example of the differences across models, consider the number-right score. The OLS model finds that a percentage point increase in the percentage of courses that are occupational during the last 2 years in high school is associated with 0.366 fewer questions answered correctly on the mathematics assessment. The conditional change model and the fixed-effects model also find a negative effect, although less pronounced than the OLS estimate: a percentage point increase in the percentage of courses that are occupational during the last 2 years in high school is associated with about 0.054 fewer questions answered correctly on the mathematics assessment. Thus, relying on the OLS model would overstate the effect of occupational coursetaking on math achievement.

Taken together, these findings suggest the presence of selection bias in both the OLS and the conditional change models, with the bias stronger in the former. The findings in both of these models are attenuated and in some cases disappear once time-invariant characteristics, observed time-varying characteristics, and time of the survey are controlled in the fixed-effects framework —making them less optimal candidates to yield the true effects of coursetaking. Additionally, conditional change models, although they more closely approximate the findings of the fixed-effects estimates than the OLS estimates, by design include a baseline measure of achievement as a right-hand side predictor. The inclusion of this lagged version of the dependent variable affects the estimates of all the predictor variables since it is likely correlated with the error term. The amount and direction of this potential bias is unclear (for relevant discussion, see Todd and Wolpin, 2003). Given these limitations, the fixed-effects specification (equation 3) is used for all estimates shown in the math achievement analysis of this report.

Dependent Variable Transformations. An assumption of linear regression is that the dependent variable is normally distributed. If violated, the model can produce biased and potentially misleading results. In preliminary analyses, the distributions of the six math achievement variables were examined. The number-right scores were normally distributed, the level 1 and 2 scores were clustered near 1.0 with a left skew, level 3 was symmetrically distributed with heavy tails, and the level 4 and 5 scores were clustered near 0.0 with a right skew.

To test whether the nonnormal distributions of the level 1, 2, 4, and 5 scores had any substantive bearing on the findings, these scores were transformed based on the shape of their distribution. The scores for level 1 and level 2 were transformed by a reflect and inverse transformation, appropriate for distributions with a sharp left skew (Tabachnick and Fidell 1996): 1 / (K – initial score), where K = largest possible value of the initial score + 1. The scores for level 4 and level 5 were transformed by an inverse transformation, appropriate for distributions with a sharp right skew (Tabachnick and Fidell 1996): 1 / initial score. All of the models presented in this report were estimated with both the original and transformed dependent variable. In all but a few instances, the findings were nearly identical when using either version of the dependent variable. None of the differences have any substantive bearing on the main findings or the conclusions. Since the coefficients are more difficult to interpret with transformed dependent variables, all the results presented in this report are based on the models that use the original metric of the dependent variable.

Standard Errors. Analyses of samples that were drawn using a cluster-stratified design, such as ELS:2002, need to correct the standard errors because the variances are smaller than they should be due to within-cluster correlation. Currently, statistical software cannot easily produce variance estimates for complex sample designs when employing panel data techniques such as the one used in this report. Instead, the standard errors were calculated using bootstrap methods, whereby the parameter estimates were produced by estimating the model 50 times on data randomly sampled from the true data. The variability in the resulting 50 slope coefficients was used as an estimate of their standard deviation. All standard errors were calculated using the cluster option in STATA to adjust for within-cluster correlation.

Control Variables. Five time-varying measures of student's time use, orientations toward school, self-efficacy in math, parental involvement, and grade retention are included in all fixed-effects regression models. Because they are not central to the research questions posed in this analysis, and because of the volume of literature that examines their relationship to achievement, they are used simply as control variables and are not reported in the tables or reviewed in the discussion. Each is measured in both the BY and the F1 interview. The construction of these measures is described below.

Math homework is a binary variable coded "1" if in an average week the student spends time on math homework outside of school and "0" if he or she does not.

Extracurricular activities is a binary variable coded "1" if in an average week the student spends time participating in extracurricular activities and "0" if he or she does not.

Employment is a binary variable coded "1" if the student ever held a job for pay and "0" if he or she has not.

Importance of education is a binary variable coded "1" if the student reported that getting a good education is very important to him or her and "0" if the student reported that getting a good education is somewhat or not important to him or her.

Expects a college degree is a binary variable coded "1" if the student reported expecting a bachelor's degree or higher and "0" if he or she reported expecting less than a bachelor's degree.

Self-efficacy in math is a standardized composite scale based on responses to the following question: "In your current or most recent math class, how often do/did the following statements apply to you?: (a) I'm confident that I can do an excellent job on my math tests; (b) I'm certain I can understand the most difficult material presented in my math text books; (c) I'm confident I can understand the most complex material presented by my math teacher; (d) I'm confident I can do an excellent job on my math assignments; and (e) I'm certain I can master the skills being taught in my math class." Response options for these five items include almost never, sometimes, often, and almost always. The scale has a Cronbach's reliability alpha of 0.91 and was created such that higher values indicate greater self-efficacy in math.

Parental involvement is a standardized composite scale based on responses to the following question: "In the first semester or term of this school year, how often have you discussed the following with either or both of your parents or guardians?: (a) selecting courses or programs at school; (b) school activities or events of particular interest to you; (c) things you've studied in class; and (d) your grades." Response options for these four items include never, sometimes, and often. The scale has a Cronbach's reliability alpha of 0.80 and was created such that higher values indicate greater parental involvement.

Grade retention is a binary variable coded "1" if the student was held back a grade between the BY and F1 interviews and "0" if he or she was not held back.

Missing Data. Selection into the analytic sample is contingent on the availability of transcript data and test scores and, therefore, there are no missing data on the measures of coursetaking and mathematics achievement. However, not all sample members have information on the time-varying measures of students' time use and orientation toward school due to item nonresponse. To maximize case coverage and to preserve the variance-covariance structure of the analytic sample, the *ice* (imputation by chained equations) multiple imputation scheme available in STATA was used. This procedure generates five data sets where missing information is imputed by regressing each variable with missing data on all observed variables with random error added to every imputed value to maintain natural variability. In the fixed-effects regression models, the estimates and their accompanying standard errors are produced using the *micombine* command in STATA that averages over the five data sets. Binary variables indicating whether the data point for a given case was observed or imputed were included in all models.

Statistical Methods: Dropping Out of High School Analysis

Discrete Time Hazard Regression. To estimate the effect of coursetaking on dropping out of high school, discrete time hazard regression models were used. In this model, the unit of analysis is a person-semester. The risk period spans six semesters (fall and spring) of each academic year; from spring 2001–02 through fall 2004–05. The construction of semesters is described later in this section. Exposure to the risk of dropping out begins in the spring of 2001–02. The dependent variable is coded 0 for all semesters in which the student is enrolled and 1 during the semester in which he or she first drops out. As is typical in hazard modeling procedures, the individual is removed from the risk set once he or she drops out (i.e., experiences the hazard event) and no longer contributes person-semesters to the analysis. Thus, an on-time student graduating in the spring of 2004 would contribute five person-semesters: spring 2001–02, fall 2002–03, spring 2002–03, fall 2003–04, and spring 2003–04. Using this analytical structure, the form of the model used in this analysis is

$$\lambda_i(t) = \lambda_0(t)e^{\sum \beta \mathbf{x}_i}$$

where λ is the rate that at which individual *i* will drop out of school during a semester given that he or she was enrolled at the start of the semester (time *t*). On the right-hand side of the equation, λ_0 is the baseline hazard rate at time *t* for all individuals in the sample when all covariates are 0. In this model, λ_0 is undefined. β is a vector of parameters associated with a vector of covariates, $\mathbf{X}_i$, which will contain both fixed and time-varying covariates. Fixed covariates include a set of time-invariant characteristics: race/ethnicity, poverty status, native language, sex, family composition, parent's level of education, student's educational expectations, grade retention, reading and mathematics test scores, grade point average in the ninth grade, academic disengagement scale, academic preparation scale, employment status, school-level poverty, region of the country, and urbanicity. The construction of these measures is described later in this section. The key time-varying covariates of interest include the current semester, the cumulative number of occupational courses earned through the most recently completed semester, the cumulative number of academic courses earned through the most recently completed semester, the percentage of courses that are classified as occupational through the most recently completed semester, the ratio of occupational courses to academic courses earned through the most recently completed semester, and the square of the ratio of occupational courses to academic courses earned through the most recently completed semester.

Standard Errors. In the discrete time hazard regression models, all standard errors were calculated using survey estimation procedures in STATA, which employ Taylor-series linearization methods to account for the clustered and stratified sampling design of ELS:2002.

The Construction of Semesters. In the transcript data file, courses were assigned credit for the term in which the course was taken. These terms include year-long courses, semester 1 (fall), semester 2 (spring), trimester 1 (fall), trimester 2 (winter), trimester 3 (spring), quarter 1 (fall), quarter 2 (fall), quarter 3 (spring), quarter 4 (spring), and summer. To properly analyze the coursetaking histories, the timing of the courses need to be calibrated into one metric. For this project, all terms were calibrated to semesters using the following criteria:

- Credits earned in semester 1 (fall), trimester 1 (fall), quarter 1 (fall), and quarter 2 (fall) were attributed to the fall semester.
- Credits earned in semester 2 (spring), trimester 3 (spring), quarter 3 (spring), and quarter 4 (spring) were attributed to the spring semester.
- Credits earned in yearlong courses were attributed to the spring semester since the acquisition of credit assumes enrollment through the end of the school year.
- Credits earned in trimester 2 (winter) were randomly assigned to one of the two semesters of the academic year.
- Credits earned with missing information on the term taken were randomly assigned to one of the two semesters of the academic year.
- Credits earned in the summer were assigned to the spring semester of the previous academic year.

Control Variables. To provide a rigorous test of the relationship between coursetaking and dropping out, a host of control variables were included in the full models. All control variables are taken from the BY data collection and, hence, temporally precede any dropout episodes. The construction of these measures is described below.

Race/Ethnicity is measured by a series of binary variables that indicate membership into one of six groups: American Indian/Alaska Native, Asian/Pacific Islander, Black or African American, Hispanic, White, and more than one race. White students serve as the reference category.

Poverty Status is reported by the student's parent and is measured by a binary variable coded "1" if the student's total family income in 2001 was $20,000 or less; otherwise coded "0."

Native Language is measured by a binary variable coded "1" if the student reported being a nonnative English speaker and "0" if the student reported being a native English speaker.

Sex is measured by a binary variable coded "1" if the student is male and "0" if the student is female.

Family Composition is reported by the student's parent and is measured by a series of binary variables: student lives with the mother and father, student lives in a stepfamily, student lives with a single parent, and student lives in another family form. Students who live with their mother and their father serve as the reference category.

Parent's Level of Education is reported by the student's parent and is measured by a series of binary variables indicating the highest level of education attained by either of the parents: high school or less, some college, a bachelor's degree, and a graduate degree. Students whose parents have earned a high school degree or less serve as the reference category.

Student's Educational Expectations are reported by the student in the 10th grade and measured by a series of binary variables indicating the highest level of education the student expects to attain: does not expect to attend college, expects to attend college but not attain a degree, and expects to attain a bachelor's degree. Students who do not expect to attend college serve as the reference category.

Grade Retention is reported by the student's parent and is measured by a binary variable coded "1" if the student was held back a grade and "0" if the student was never held back a grade.

Reading and Mathematics Test Scores are based on standardized reading and mathematics assessments given to the students in the spring of 2001–02. The scores were standardized and averaged to form a continuous composite achievement score where higher scores indicate higher achievement.

Grade Point Average in the Ninth Grade is a continuous measure based on student's grades in all courses during the ninth grade as reported on their transcript. Grades are based on a four-point scale ranging from 0 to 4 (0.0 = F; 4.0 = A).

Academic Disengagement Scale is a composite based on student's reports to four questions: (1) How many times during the first semester or term of this school year were you late for school?; (2) How many times during the first semester or term of this school year did you cut or skip class?; (3) How many times during the first semester or term of this school year were you absent from school?; and (4) How much do you agree or disagree with the following statement?: "I go to school because the subjects I am taking are interesting or challenging." Responses to the first three questions were coded "1" for never, "2" for 1–2 times, "3" for 3–6 times, "4" for 7–9 times, and "5" for 10 or more times. Responses to the fourth question were coded "1" for strongly agree, "2" for agree, "3" for disagree, and "4" for strongly disagree. Responses to all four questions were standardized and averaged to form a single continuous composite where higher values indicate greater levels of academic disengagement. The alpha coefficient for the scale is 0.59.

Academic Preparation Scale is a composite based on student's reports to three questions: (1) How often do you come to class without pencil, pen, or paper?; (2) How often do you come to class without books?; and (3) How often do you come to class without your homework done? Responses to these questions were coded "1" for never, "2" for seldom, "3" for often, and "4" for usually. Responses to all three questions were standardized and averaged to form a single continuous composite where higher values indicate lower levels of academic preparation. The alpha coefficient for the scale is 0.81.

Employment Status is reported by the student and is measured by a series of binary variables indicating whether he or she had ever worked for pay, excluding work done around the house: never employed, currently employed, and has been employed but is not currently employed. Students who have never been employed serve as the reference category.

Homework is a student-reported continuous measure ranging from 0 to 26 indicating the number of hours both in and out of school they spent on homework in an average week.

School-level Poverty is taken from the Common Core of Data and indicates the proportion of students in the student's 10th-grade school who qualify for free or reduced-price lunch. The distribution was divided into quartiles. In this analysis, school-level poverty is measured by a series of binary variables indicating the quartiles: quartile 1 (low poverty), quartile 2, quartile 3, and quartile 4 (high poverty). Students attending low-poverty schools serve as the reference category.

Region is measured by a series of binary variables indicating the location of the student's 10th-grade school: Northeast, Midwest, South, and West. Students attending schools in the Northeast serve as the reference category.

Urbanicity is measured by a series of binary variables indicating the location of the student's 10th-grade school: urban area, rural area, and suburban area. Students attending schools in urban areas serve as the reference category.

Missing Data. As in the mathematics achievement analysis, the *ice* multiple imputation scheme available in STATA was used to maximize case coverage and to preserve the variance-covariance structure of the analytic sample. This procedure generates five data sets where missing information is imputed by regressing each variable with missing data on all observed variables with random error added to every imputed value to maintain natural variability. In the discrete time hazard regression models, the estimates and their accompanying standard errors are produced using the *micombine* command in STATA that averages over the five data sets. Binary variables indicating whether the data point for a given case was observed or imputed were included in all models.

Statistical Methods: School Context Analysis

Multilevel Models. Information about variables and missing data for the analysis of school context can be found in the above respective sections on the mathematics achievement and dropping out analysis methods. This section discusses multilevel modeling.

In order to understand whether school context affects math achievement or the likelihood of dropping out, methods that explicitly take into account the clustering of students within schools are required. Multilevel modeling (also called hierarchical linear modeling) is a modeling approach that takes account of this clustering and makes it possible to directly estimate the effects of school context on individual outcomes. In the current case, multilevel models can help pinpoint the influence of attendance at a full-time CTE school or a school in a rural area on math achievement and dropping out.

Multilevel models may be thought of as consisting of two or more levels, depending on the hierarchical structure of the data. In the case where students are clustered in one higher-level group like schools, two levels are involved: the individual level (students) and the group level (schools). More complex multilevel models can be created that include additional levels such as classrooms (with students and schools, making a three-level model) or other entities like districts or states (adding additional levels). Here, we use a two-level model involving students and schools (in ELS:2002, students are not sampled by classrooms, so no grouping information at that level is available).

In its basic form, the two-level model consists of a level-1 model that is structured similarly to a typical single-level regression model, to wit:

$$Y_{ij} = B_{0j} + B_1X_{1ij} + B_2X_{2ij} + \dots B_pX_{pij} + R_{ij} \qquad \text{(equation 1)}$$

Where Y_{ij} is the outcome for the *i*th student in group *j*, B_{0j} is the intercept (or average outcome after the effects of independent variables are taken out) for group *j*, X_{1ij} to X_{pij} represent the independent variables with their associated coefficiencts (B_1 to B_p), and R_{ij} is the usual residual error term. The main difference between a multilevel model and single-level regression model here is that the intercept represents both a fixed component that is the same for all groups and a random component that varies across groups, so that each group has its own intercept.

In addition to the level-1 model, a level-2 model is estimated:

$$B_{0j} = \gamma_{00} + \gamma_{01}Z_{1j} + \gamma_{02}Z_{2j} + \dots \gamma_{0q}Z_{qj} + U_{0j} \qquad \text{(equation 2)}$$

Where γ_{00} is the fixed intercept for all groups, Z_{1j} to Z_{qj} are any level-2 variables with their associated coefficients (γ_1 to γ_q), and U_{0j} is a random error term. This model indicates that the level 2 variables (Zs) are predicting the intercept for the level-1 variable. More complex multilevel models (not used here) could also allow level-2 variables to predict other level-1 coefficiencts (B_1 to B_p), with each predicted B coefficient having their own representation in a level-2 equation. It is also possible for no level-2 variables (Zs) to be included in equation 2, so that only the fixed intercept for all groups (γ_{00}) and the random component unique to each group (U_{0j}) are included and estimated. In the following analyses, this model (a random intercepts model) will be used to estimate the amount of math achievement and dropout variation that exists within and across schools (a kind of baseline amount of variation that indicates how much variation can be explained by our level-2 school variables).

Equation 2 as written can be substituted into equation 1 to yield a combined equation that summarizes the multilevel model:

$$Y_{ij} = \gamma_{00} + B_{0j} + B_1X_{1ij} + B_2X_{2ij}\ldots B_pX_{pij} + \gamma_{01}Z_{1j} + \gamma_{02}Z_{2j}\ldots \gamma_{0q}Z_{qj} + R_{ij} + U_{0j} \text{ (eq.3)}$$

In equation 3, the outcome is predicted both by individual-level variables (in the current analysis, student-level) and by group-level (school) variables. In the models used for this analysis, a similar equation was used to predict the selected outcomes, but with either the full-time CTE school indicator variable or rural school indicator variable being the only level-2 variable in the model.

Analysis techniques compared with prior models. For the math achievement models, multilevel models are employed without taking into account the same within-person factors that the fixed effects models employed previously. This is done because such an advanced model introduces complexities that are not necessary to answer the basic question posed: whether the effects of CTE coursetaking differ by school context. Though coefficients may be biased by unobserved heterogeneity (the situation for which the earlier fixed effects models accounted), the statistical significance of coefficients is not (Allison 1995, p. 236), and therefore the basic question can be addressed and answered in the context of a conditional change model as described in the "Mathematics achievement analysis" section above. In this case, grade 12 math achievement is the outcome, and grade 10 achievement score is an additional predictor. In addition, only a single set of multiply imputed data were used with this analysis, due to limitations of event-history estimation software in combining multiple imputed regression results.

For models of dropping out, multilevel models can be fitted that are also discrete-time event history models, and this type of model is necessary to ensure the accuracy of estimates. In this case, multilevel event history models can be estimated using discrete-outcome event history structural forms (e.g., logit or probit regression, in the same way that single-level event history models of discrete outcomes may be estimated with cross-sectional discrete-outcome forms like logit regression) (Barber et al. 2000; Guo and Zhao 2000). In the current analysis, logistic regression serves as the basis for the multilevel event-history models. However, due to the complexity of these models and the lack of support in statistical analysis software packages, results do not include direct standard error corrections for the complex survey design; however, the multilevel modeling procedures themselves take into account school-based clustering. Finally, only a single set of multiply imputed data were used with this analysis.

Since model results for variables not of interest in this chapter (i.e., timing variables, student controls, and other school controls) largely replicated previous analyses, these are not presented in appendix C. Full model results for the multilevel analyses are available from the authors upon request.

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Appendix B
Classification of Courses

Academic Courses

The academic curriculum contains six subject areas: mathematics, science, English, social studies, fine arts, and non-English language. Courses within each subject area along with their Classification of Secondary School Course (CSSC) code are listed below.

Mathematics

CSSC Code	Course Title
010151	Agricultural Mathematics
070171	Business Mathematics 1
070172	Business Mathematics 2
170651	Nurse’s Mathematics
270100	Mathematics, Other General
270101	Mathematics 7
270102	Mathematics 7, Accelerate
270103	Mathematics 8
270104	Mathematics 8, Accelerated
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
270200	Actuarial Sciences, Other
270300	Applied Mathematics, Other
270400	Pure Mathematics, Other
270401	Pre-Algebra
270402	Algebra 1, Part 1
270403	Algebra 1, Part 2
270404	Algebra 1
270405	Algebra 2
270406	Geometry, Plane
270407	Geometry, Solid
270408	Geometry
270409	Geometry, Informal
270410	Algebra 3
270411	Trigonometry
270412	Analytic Geometry
270413	Trigonometry and Solid Geometry
270414	Algebra and Trigonometry
270415	Algebra and Analytic Geometry
270416	Analysis, Introductory
270417	Linear Algebra
270418	Calculus and Analytic Geometry
270419	Calculus
270420	AP Calculus
270421	Mathematics 1, Unified
270422	Mathematics 2, Unified
270423	Mathematics 3, Unified
270424	Mathematics, Independent Study
270425	Geometry, Part 1
270426	Geometry, Part 2
270427	Unified Mathematics 1, Part 1
270428	Unified Mathematics 1, Part 2
270429	Pre-IB Geometry
270430	Pre-IB Algebra 2/Trigonomery
270431	IB Mathematics Methods 1
270432	IB Mathematics Studies 1
270433	IB Mathematics Studies 2
270434	IB Mathematics Studies/Calculus
270435	AP Calculus CD

270441	Algebra and Geometry
270500	Statistics, Other
270511	Statistics
270521	Probability
270531	Probability and Statistics
270532	AP Statistics
270601	Basic Mathematics 1
270602	Basic Mathematics 2
270603	Basic Mathematics 3
270604	Basic Mathematics 4
279900	Mathematics, Other
541001	General Mathematics Skills
541009	Functional Mathematics Skills, not for credit
541101	Functional Consumer Mathematics
541109	Functional Consumer Mathematics, not for credit
541201	Functional Vocational Mathematics
541209	Functional Vocational Mathematics, not for credit
562700	Special Education Mathematics
562701	Resource General Mathematics
562709	Resource General Mathematics, not for credit
562711	Resource Vocational Mathematics
562719	Resource Vocational Mathematics, not for credit
562721	Resource Consumer Mathematics
562729	Resource Consumer Mathematics, not for credit

Science

CSSC Code	Course Title
140100	Engineering, Other General
140111	Orientation to Engineering
140200	Aerospace, Aeronautical, and Astronautical Engineering, Other
140211	Aerospace Materials
140221	Aerospace Engineering Design
140300	Agricultural Engineering, Other
140400	Architectural Engineering, Other
140411	Strength of Materials – Architectural
140500	Bioengineering and Biomedical Engineering, Other
140600	Ceramic Engineering, Other
140700	Chemical Engineering, Other
140800	Civil Engineering, Other
140900	Computer Engineering, Other
141000	Electrical, Electronics and Communications Engineering, Other
141100	Engineering Mechanics, Other
141200	Engineering Related, Other
141211	Instrumentation Physics 1
141212	Instrumentation Physics 2
141213	Instrumentation Physics 3
141214	Instrumentation Physics 4 /Advanced Placement
141300	Engineering Science, Other
141400	Environmental Health Engineering, Other
141500	Geological Engineering, Other
141600	Geophysical Engineering, Other
141700	Industrial Engineering, Other
141800	Materials, Engineering, Other
141900	Mechanical Engineering, Other
141911	Strength of Materials, Mechanical Technology
142000	Metallurgical Engineering, Other
142011	Metallurgy/Powder Metal Basics
142100	Mining and Mineral Engineering, Other
142200	Naval Architecture and Marine Engineering, Other
142300	Nuclear Engineering, Other
142400	Ocean Engineering, Other
142500	Petroleum Engineering, Other
142600	Surveying and Mapping Sciences, Other
142611	Cartography
142700	Systems Engineering, Other

142800	Textile Engineering, Other
149900	Engineering, Other
182501	Bio-Medical Technology, General
260100	Biology, Other General
260111	Science 7
260121	Biology, Basic 1
260122	Biology, Basic 2
260131	Biology, General 1
260132	Biology, General 2
260141	Biology, Honors 1
260142	Biology, Advanced
260143	Pre-IB Biology
260144	IB Biology 2
260145	IB Biology 3
260146	AP Biology
260151	Field Biology
260161	Genetics
260171	Biopsychology
260181	Biology Seminar
260200	Biochemistry and Biophysics, Other
260211	Biochemistry
260300	Botany, Other
260311	Botany
260400	Cell and Molecular Biology, Other
260411	Cell Biology
260500	Microbiology, Other
260511	Microbiology
260600	Miscellaneous Specialized Areas, Life Sciences, Other
260611	Ecology
260621	Marine Biology
260622	Marine Biology, Advanced
260631	Anatomy
260700	Zoology, Other
260711	Zoology
260721	Zoology, Vertebrate
260731	Zoology, Invertebrate
260741	Animal Behavior
260751	Physiology, Human
260752	Physiology, Advanced
260761	Pathology
260771	Comparative Embryology
269900	Life Sciences, Other
300100	Biological and Physical Sciences, Other
300111	Science, Unified
300112	College Pre-Science Skills
300121	Science Study, Independent
300300	Engineering and Other Disciplines, Other
300311	Engineering Concepts
300623	IB Environmental Studies
400100	Physical Sciences, Other General
400111	Science 8
400121	Physical Science
400131	Chemistry and Physics Laboratory Techniques
400141	Physical Science, Applied
400200	Astronomy, Other
400211	Astronomy
400300	Astrophysics, Other
400411	Meteorology
400500	Chemistry, Other
400511	Chemistry, Introductory
400512	Chemistry in the Community
400521	Chemistry 1
400522	Chemistry 2
400523	Pre-IB Chemistry 1
400524	IB Chemistry 2
400525	IB Chemistry 3
400526	AP Chemistry
400531	Organic Chemistry
400541	Physical Chemistry
400551	Consumer Chemistry
400561	Chemistry, Independent Study
400600	Geological Sciences, Other
400611	Earth Science
400621	Earth Science, College Preparatory
400622	AP Environmental Science
400631	Geology
400632	Geology – Field Studies

400641	Mineralogy
400700	Miscellaneous Physical Sciences, Other
400711	Oceanography
400800	Physics, Other
400811	Physics, General
400812	Principles of Technology 1
400813	Principles of Technology 2
400821	Physics 1
400822	Physics 2
400823	IB Physics
400824	AP Physics B
400825	AP Physics C: Mechanics
400826	AP Physics C: Electricity/Magnetism
400831	Physics 2 without Calculus
400841	Electricity and Electronics Science
400851	Acoustics
400900	Planetary Science, Other
400911	Rocketry and Space Science
401011	Aerospace Science
409900	Physical Sciences, Other
410211	Radioactivity
544001	Functional Science
544009	Functional Science, not for credit
564000	Special Education General Science
564001	Resource General Science
564009	Resource General Science, not for credit

English

CSSC Code	Course Title
070411	Business English 1
070412	Business English 2
070413	Business English 3
070414	Business English 4
090400	Journalism (Mass Communications), Other
090411	Journalism 1
090412	Journalism 2
090413	Journalism 3
090421	Journalism Investigations
090431	Literary Magazine
160121	English as a Second Language 1
160122	English as a Second Language 2
160123	English as a Second Language 3
160124	English as a Second Language, Skills Lab
160125	Transitional English
230100	English, Other General
230101	English 7
230102	English 7, Honors
230103	English 8, Below Grade Level
230104	English 8
230105	English 8, Honors
230106	English 1, Below Grade Level
230107	English 1
230108	English 1, Honors
230109	English 2, Below Grade Level
230110	English 2
230111	English 2, Honors
230112	English 3, Below Grade Level
230113	English 3
230114	English 3, Honors
230115	English 4, Below Grade Level
230116	English 4
230117	English 4, Honors
230118	World Literature
230119	Renaissance Literature
230120	Romanticism
230121	Realism
230122	Literature, Contemporary
230123	Irish Literature
230124	Russian Literature
230125	Bible as Literature
230126	Mythology and Fable
230127	Drama, Introduction

230128	World Drama
230129	Plays, Modern Survey
230130	Novels
230131	Short Story
230132	Mysteries
230133	Poetry
230134	Rock Poetry
230135	Humor
230136	Biography
230137	Non Fiction
230138	Science Fiction
230139	Themes in Literature
230140	Literature of Human Values
230141	Ethnic Literature
230142	Women in Literature
230143	Sports through Literature
230144	Occult Literature
230145	Protest Literature
230146	Youth and Literature
230147	Heroes
230148	Utopias
230149	Death
230150	Nobel Prize Authors
230151	Seminar on an Author
230152	English, Real Life Problem Solving
230153	Reading, Independent Study
230154	Research Technique
230155	Children's Literature & Fantasy
230156	Vocational English
230161	Pre-IB English 1 (grade 9)
230162	Pre-IB English 2 (grade 10)
230163	Pre-IB English 3 (grade 11)
230164	IB English 4 (grade 11 or 12)
230165	IB English 5 (grade 12)
230166	AP Language and Composition
230167	AP Literature and Composition
230171	English 1/History
230172	English 2/History
230173	English 3/History
230200	Classics, Other
230211	Mythological Literature, Greek and Roman
230300	Comparative Literature, Other
230311	Comparative Literature
230321	Latin American Authors/Literature
230400	Composition, Other
230401	Composition, Expository
230402	Writing Laboratory
230403	Writing About Literature
230404	Vocabulary
230405	Spelling
230406	Grammar 7
230407	Grammar 8
230408	Grammar 9
230409	Grammar 10
230410	Grammar 11
230411	Grammar 12
230412	Etymology
230415	Word Study – Remedial
230500	Creative Writing, Other
230511	Creative Writing 10
230512	Creative Writing 11
230513	Creative Writing 12
230521	Creative Writing, Independent Study
230600	Linguistics (includes Phonetics, Semantics, and Philology), Other
230611	Linguistics
230700	Literature, American, Other
230711	American Literature
230721	Black Literature
230731	American Dream in Literature
230741	Folklore, American
230751	Indian Literature
230761	State Writers
230771	Western Literature
230781	Mexican American Literature
230800	Literature, English, Other
230811	British Literature Survey
230821	Shakespeare

230831	Modern British Writer
230841	Victorian Literature
230851	Satire, Modern British
230861	Arthurian Legend
230871	Medieval Literature
230900	Rhetoric, Other
231000	Speech, Debate, and Forensics, Other
231011	Public Speaking
231021	Speech 1
231022	Speech 2
231023	Speech 3
231031	Debate Practicum Contract
231100	Technical and Business Writing, Other
231111	Technical English
231211	Reading Development 1
231212	Reading Development 2
231213	Reading Development 3
231214	Reading Development 4
231216	Advanced Reading and Study Skills
231311	Functional English 1
231312	Functional English 2
231313	Functional English 3
231314	Functional English 4
239900	Letters/English, Other
542011	Functional Language Arts
542019	Functional Language Arts 1, not for credit
542021	Functional Language Arts 2
542029	Functional Language Arts 2, not for credit
542031	Functional Language Arts 3
542039	Functional Language Arts 3, not for credit
542041	Functional Language Arts 4
542049	Functional Language Arts 4, not for credit
542051	Functional Vocational English
542059	Functional Vocational English, not for credit
542101	Functional Reading
542109	Functional Reading, not for credit
542201	Functional Oral Communication
542209	Functional Oral Communication, not for credit
542301	Functional Writing
542309	Functional Writing, not for credit
562300	Special Education Language Arts
562301	Resource Language Arts/English
562302	Developmental English 2/Resource ESE AAP English 2
562304	Developmental English 4/Resource ESE AAP English 4
562309	Developmental English 4/Resource ESE AAP English 4
562310	Special Education Reading
562311	Resource Writing
562319	Resource Reading, not taken for credit
562320	Special Education Writing
562321	Resource Writing
562329	Resource Writing, not for credit

Social Studies

CSSC Code	Course Title
050100	Area Studies, Other
050101	Area Studies
050102	American Studies, Basic
050103	American Studies, General
050104	America's People and Problems
050105	American Studies, Honors
050106	New England Studies
050107	Old South
050108	American West
050109	Southwest United States
050110	Anglo America
050111	North America and Current Events
050112	North and South America
050113	Latin America
050114	World Studies 1
050115	World Studies 2
050116	World Studies, Honors
050117	Comparative World Cultures
050118	European Culture Studies, Basic
050119	European Culture Studies, General
050120	European Culture Studies, Honors
050121	Developing Nations
050122	African Area Studies
050123	Africa and South America
050124	Asian and African Cultural Studies, Basic
050125	Asian and African Cultural Studies, General
050126	Asian and African Cultural Studies, Honors
050127	Asian Studies
050128	History of China
050129	Asia, Africa and Mideast
050130	Africa and Middle East
050131	Middle Eastern Studies
050132	Middle East, War for Survival
050133	USSR
050134	Soviet Union and China
050135	Soviet Union and Afro American Developing Nations
050136	History of Russia
050137	Neglected World
050138	Global Education
050139	Pacific Rim Nations
050140	Canadian Area Studies
050200	Ethnic Studies, Other
050211	Minorities in America
050221	Ethnic and Family Heritage
050231	Afro American Studies
050241	Economics of Afro Americans
050251	Indians of North America
050261	Jewish Historical Significance
050271	Mexican American Heritage
050281	Hawaiiana
050291	Hawaiian Culture Studies, Modern
059900	Area and Ethnic Studies, Other
090121	Intercultural Communications
090500	Public Relations, Other
220100	Law, Other
220111	Law Fundamentals
220121	Law and You
220131	Street Law
230171	English 1/History

230172	English 2/History
230173	English 3/History
240100	Liberal/General Studies, Other
240111	Liberal Studies
300400	Humanities and Social Sciences, Other
300411	Humanities
300421	Humanities, European
300431	Humanities, American
300441	Humanities, African
300451	Humanities, Near East and Far East
300500	Peace Studies, Other
300600	Systems Science, Other
300611	Futuristics
300621	Environmental Science
300700	Women's Studies, Other
300711	Women's Studies
300721	Women's Studies in Literature
309900	Multi/Interdisciplinary Studies, Other
380100	Philosophy, Other
380111	Philosophy
380121	Ethics
380131	Logic
380141	Epistemics
380142	IB Theory of Knowledge
380151	Social Justice Issues
420100	Psychology, Other General
420111	Psychology
420112	Psychology, Advanced
420113	Abnormal Psychology
420114	AP Psychology
420115	IB Psychology
420200	Clinical Psychology, Other
420300	Cognitive Psychology, Other
420311	Psychology of Learning
420321	Educational Psychology
420400	Community Psychology, Other
420500	Comparative Psychology, Other
420600	Counseling Psychology, Other
420700	Developmental Psychology, Other
420711	Child Psychology
420721	Adolescent Psychology
420731	Adjustment Psychology
420800	Experimental Psychology, Other
420900	Industrial and Organizational Psychology, Other
421000	Personality Psychology, Other
421011	Historical Personalities and Ideas
421021	Humanistic Psychology
421100	Physiological Psychology, Other
421200	Psycholinguistics, Other
421300	Psychometrics, Other
421400	Psychopharmacology, Other
421411	Psychopharmacology
421500	Quantitative Psychology, Other
421600	Social Psychology, Other
421611	Social Psychology
429900	Psychology, Other
440300	International Public Service, Other
450100	Social Sciences, Other General
450111	Social Science, Introduction
450121	Social Science, Advanced Theory and Research
450131	Social Science Seminar
450141	Social Studies, Independent Study
450200	Anthropology, Other
450211	Anthropology
450221	Comparative Cultural Patterns
450231	Anthropology, Myth and Magic
450241	Cultural Anthropology, Research
450300	Archaeology, Other

450311	Archaeology
450500	Demography, Other
450511	Population Education
450600	Economics, Other
450601	Economics, Theory
450602	Economics and Economic Problems
450603	Consumer Economics
450605	Insurance Theory
450606	Investment Economics
450607	Television and Economics
450608	Energy Education
450609	American Labor History
450610	Economics, Analysis and Criticism
450611	Economics, College
450612	International Economics
450613	AP Economics; AP Microeconomics
450614	AP Macroeconomics
450615	IB Microeconomics
450616	IB Macroeconomics
450700	Geography, Other
450701	Geography 8
450702	Geography, United States
450703	Geography, North American
450704	World Geography
450705	Geography, Western Hemisphere and Africa
450706	Geography, Eastern Hemisphere
450707	Physical Geography
450708	Economic and Political Geography
450709	Human and Cultural Geography
450710	Field Geography, Honors
450711	IB World Geography
450712	AP Human Geography
450800	History, Other
450801	History and Geography 7
450802	Our Cultural Heritage 7
450803	Social Studies 7, Honors
450804	United States History 8
450805	Social Studies 8
450806	Social Studies 8, Honors
450807	United States History, State and Local
450808	United States History, Advanced Placement
450809	American History, Basic
450810	American History
450811	United States History 1
450812	United States History 2
450813	United States History, Honors
450814	American History, Advanced Placement
450815	Westward Movement
450816	Twentieth Century America
450817	Twenties and Thirties
450818	America Since 1945
450819	Nineteen Sixties
450820	Nineteen Seventies
450821	Reform in American History
450822	American Inquiries
450823	Historic Events, United States
450824	American Wars, Causes and Effects
450825	Civil War
450826	Civil War, Reconstruction and Industrialism
450827	War and Modern Consciousness
450828	World War II
450829	United States Military History 1
450830	United States Military History 2
450831	United States History, Field Study
450832	North American History
450833	Mexican History
450834	South American History
450835	World History

450836	World History, College
450837	World History, Modern
450838	World Civilization, 20th Century
450839	World Civilization, 20th Century, Honors
450840	Western Civilization 9
450841	Western Civilization 9, Honors
450842	Western Civilization, History
450843	Early Western Civilization
450844	World History, Advanced
450845	Ancient and Classical World
450846	Ancient Greek History
450847	Rome and Her Empire
450848	Ancient History and Middle Ages
450849	English History
450850	English History, Honors
450851	French Revolution, Honors
450852	Modern Europe
450853	European History, Mid-19th Through Mid-20th Centuries, Advanced Placement
450854	European History, 20th Century
450855	European History, Advanced Readings
450856	European History, Modern
450857	Third World History
450858	African History
450860	Latin American History
450861	Middle East History
450862	Israel, History
450863	Eastern Civilization
450864	Far East, History
450865	Asian History, Modern
450866	Pacific Lands, History
450867	Russian History
450868	World Leaders, Past and Present
450869	Historical Research
450870	Pre-IB World History
450871	IB History Of The Americans
450872	IB Twentieth Century World Topics
450873	IB History of Europe
450874	Pre-IB US History
450875	AP World History
450881	The Holocaust
450900	International Relations, Other
450911	International Relations
450921	International Relations, Honors
450931	International Law
450941	Model Security Council, Local
450951	Model United Nations, Local
450952	Model United Nations, National
451000	Political Science and Government, Other
451001	Civics
451002	State and Local Government
451003	Government, Basic
451004	American Government
451005	Presidency
451006	Framework of the Constitution
451007	Individual vs. State
451008	National State and Local Elections
451009	Elections, Politics and Morality, Honors
451010	Contemporary World Affairs
451011	American Foreign Policy
451012	Decision Making in a Crisis
451013	American Heritage, Honors
451014	Contemporary American Political Issues
451015	Contemporary American Political Issues, Honors
451016	American Government and Economics, Basic
451017	American Government and Economics
451018	American Government and Economics, Honors
451019	Comparative Political Systems, Basic

451020	Comparative World Governments
451021	Americanism vs. Communism
451022	Americanism vs. Communism, Honors
451023	Communism and Its Growth
451024	Civics, Honors
451025	Writings Influencing Government
451026	Government Internship
451027	Model Senate
451028	Political Leadership
451029	Political Science
451030	Political Science, Advanced Placement
451031	Political Science and Government – Local/Regional Government Field
451032	Political Turmoil
451033	Contemporary Issues, Basic Skills
451034	Pre-IB American Government/Economics
451035	AP American Government and Politics
451036	AP Comparative Government and Politics
451037	IB American Government
451100	Sociology, Other
451111	American Social Problems, Introduction
451121	Sociology, General
451131	Sociology, Issues
451132	The Poor in America
451141	Mobility in Society
451151	Violence In America
451161	Death and Dying
451171	Sociology, Honors
451181	Sociology, Research
451200	Urban Studies, Other
451211	Urban Problems
451221	Urban Ecology
451231	Technology and Urbanization
459900	Social Sciences, Other
564500	Special Education Social Studies
564501	Resource Social Studies
564509	Resource Social Studies, not for credit

Fine Arts

CSSC Code	Course Title
500100	Visual and Performing Arts, Other General
500111	Aesthetics
500200	Crafts, Other
500211	Crafts 7
500212	Crafts 8
500213	Crafts 9
500214	Crafts 10
500215	Crafts 11
500216	Crafts 12
500221	Crafts 11, Advanced
500222	Crafts 12, Advanced
500231	Decorator Crafts
500241	Enameling
500251	Jewelry 1
500252	Jewelry 2
500253	Jewelry 3
500254	Jewelry 4
500262	Ceramics 8
500263	Ceramics 9
500264	Ceramics 10
500265	Ceramics 11
500266	Ceramics 12
500271	Textile Design
500281	Model Building
500291	Printmaking 1
500292	Printmaking 2
500300	Dance, Other
500311	Modern Dance for Beginners 9
500312	Modern Dance for Beginners 10
500313	Modern Dance for Beginners 11
500314	Modern Dance for Beginners 12
500321	Modern Dance 9, Intermediate
500322	Modern Dance 10, Intermediate
500323	Modern Dance 11, Intermediate
500324	Modern Dance 12, Intermediate
500331	Dance 9, Advanced
500332	Dance 10, Advanced
500333	Dance 11, Advanced
500334	Dance 12, Advanced
500335	Advanced Dance IB
500341	Performing Dance Group 9
500342	Performing Dance Group 10
500343	Performing Dance Group 11
500344	Performing Dance Group 12
500351	Ballet and Jazz for Beginners 9
500352	Ballet and Jazz for Beginners 10
500353	Ballet and Jazz for Beginners 11
500354	Ballet and Jazz for Beginners 12
500361	Ethnic Dance
500371	Square Dance
500381	Aerobic Dance
500421	Theater Makeup
500431	Lighting Fundamentals, Theater
500500	Dramatic Arts, Other
500511	Stagecraft 9
500512	Stagecraft 10
500514	Stagecraft 12
500521	Improvisation and Mime
500531	Playwriting
500541	Theater Practicum Contract
500551	Drama, History
500561	Drama, Independent Study
500600	Film Arts, Other
500611	Film Study
500612	Language of the Cinema
500621	Photography 10
500622	Photography 11, Elementary
500623	Photography 12, Elementary
500631	Photography 11, Advanced
500632	Photography 12, Advanced

500700	Fine Arts, Other	500907	Band 9
500701	Fine Arts 7	500908	Band 9, Advanced
500702	Fine Arts 8	500909	Band, Concert
500703	Art, General	500910	Band, Marching
500704	Art 1	500911	Band, Symphonic
500705	Art 2	500912	Orchestra 7
500706	Art 3	500913	Orchestra 7, Advanced
500707	Art 4	500914	Orchestra 8
500708	Art 1, Independent Study	500915	Orchestra 8, Advanced
500709	Art 2, Independent Study	500916	Orchestra 9
500711	Art Services 10	500917	Orchestra 9, Advanced
500712	Art Services 11	500918	Orchestra 10
500713	Art Services 12	500919	Orchestra 11
500714	Drawing	500920	Orchestra 12
500715	Painting 1	500921	Instrumental String Class
500716	Painting 2	500922	Brass and Percussion Class
500717	Watercolor 1	500923	Wind Ensemble
500718	Cartooning	500924	Woodwind Class
500719	Mural Painting	500925	Electronic Music, Introduction
500720	Sculpture	500926	Ensemble, Instrumental
500721	Silk Screen	500927	Guitar, Beginning
500722	Assemblage	500928	Guitar, Intermediate
500723	Product Design	500929	Guitar, Advanced
500724	Life Drawing	500930	Handbells
500725	Calligraphy	500931	Piano 1
500726	Art History and Appreciation	500932	Piano 2
500727	Black Fine Arts	500933	Organ
500728	Mexico, Fine Arts	500934	Music Lessons, Applied
500729	Bicultural Art	500935	Chorus 7
500730	Artist in Residence Program	500936	Chorus 7, Advanced
500731	Ethnic Art History	500937	Chorus 8
500732	Art As A Multicultural Study	500938	Chorus 8, Advanced
500900	Music, Other	500939	Chorus 9
500901	Music 7	500940	Chorus 9, Advanced
500902	Music 8	500941	Chorus 10
500903	Band 7	500942	Chorus 10, Advanced
500904	Band 7, Advanced	500943	Chorus 11
500905	Band 8	500944	Chorus 11, Advanced
500906	Band 8, Advanced	500945	Chorus 12

500946	Chorus 12, Advanced
500947	Vocal Ensemble
500948	Voice Class
500949	Harmony and Composition
500950	Arranging
500951	Conducting
500952	Music Theory
500953	Music History 7
500954	Music History 8
500955	Music History 9
500956	Music History 10
500957	Music History 11
500958	Music History 12
500959	Music Literature 9
500960	Music Literature 10
500961	Music Literature 11
500962	Music Literature 12
500963	Music Appreciation
500964	Folk Music, Ethnic
500965	Music Theater
500966	Music, Independent Study
500967	Music Laboratory, General Survey
509900	Visual and Performing Arts, Other

Non-English Language

CSSC Code	Course Title
090811	Sign Language 1
090812	Sign Language 2
090813	Sign Language 3
090821	Braille Communications
160200	African (Non-Semitic) Languages, Other
160211	Swahili 1
160212	Swahili 2
160221	Amharic 1 (Ethiopian)
160222	Amharic 2 (Ethiopian)
160300	Asiatic Languages, Other
160311	Cantonese 1
160312	Cantonese 2
160313	Cantonese 3
160314	Cantonese 4
160321	Mandarin 1
160322	Mandarin 2
160323	Mandarin 3
160324	Mandarin 4
160325	Mandarin 5
160326	IB Chinese
160331	Japanese 1
160332	Japanese 2
160333	Japanese 3
160334	Japanese 4
160335	Japanese 5
160336	Foreign Language Contract, Japanese
160337	IB Japanese 4
160338	IB Japanese 5
160341	Hawaiian 1
160342	Hawaiian 2
160343	Hawaiian 3
160344	Hawaiian 4
160345	Hawaiian Language and Culture
160351	Korean 1
160352	Korean 2
160353	Korean 3
160354	Korean 4
160355	Korean 5
160400	Balto-Slavic Languages, Other
160411	Ukrainian 1
160421	Russian 1
160422	Russian 2
160423	Russian 3
160424	Russian 4
160425	Russian 5
160426	Russian 6

160427	Foreign Language Contract, Russian
160431	Czech 1
160432	Czech 2
160433	Czech 3
160441	Polish 1
160442	Polish 2
160443	Polish 3
160444	Polish 4
160451	Finnish 1
160452	Finnish 2
160453	Finnish 3
160454	Finnish 4
160500	Germanic Languages, Other
160501	Dutch 1
160502	Dutch 2
160503	Dutch 3
160511	German 7
160512	German 8
160513	German 1
160514	German 2
160515	German 3
160516	German 4
160517	German 5
160518	German Field-Based Experience
160519	Foreign Language Contract, German
160521	Norwegian 1
160522	Norwegian 2
160531	Swedish 1
160532	Swedish 2
160533	Swedish 3
160541	Yiddish 1
160542	Yiddish 2
160543	Yiddish 3
160544	IB German 4
160545	IB German 5
160546	AP German Language
160600	Greek, Other
160611	Modern Greek for Survival
160621	Modern Greek
160622	Modern Greek 2
160623	Modern Greek 3
160624	Modern Greek 4
160631	Classical Greek 1
160632	Classical Greek 2
160633	Classical Greek 3
160634	Classical Greek 4
160700	Indic Languages, Other
160800	Iranian Languages, Other
160900	Italic Languages, Other
160901	French 7
160902	French 8
160903	French 1
160904	French 2
160905	French 3
160906	French 4
160907	French 5
160908	French Field-Based Experience
160909	Foreign Language Contract, French
160910	French, Conversational
160911	Italian 7
160912	Italian 8
160913	Italian 1
160914	Italian 2
160915	Italian 3
160916	Italian 4
160917	Italian, Advanced Placement
160918	Italian Field-Based Experience
160919	Foreign Language Contract, Italian
160920	Latin 1
160921	Latin 2
160922	Latin 3
160923	Latin 4
160924	Latin 5
160925	Foreign Language Contract, Latin
160926	Portuguese 1
160927	Portuguese 2
160928	Portuguese 3
160929	Portuguese 4

160930	Portuguese 5
160931	Spanish 7
160932	Spanish 8
160933	Spanish 1
160934	Spanish 2
160935	Spanish 3
160936	Spanish 4
160937	Spanish 5
160938	Spanish Field-Based Experience Spanish Seminar
160939	Foreign Language Contract, Spanish
160941	Spanish for Travelers
160942	Spanish, Commercial Spanish, Job Related
160943	IB French Language
160944	IB French Literature
160945	IB Spanish 4
160946	IB Spanish 5
160947	AP Latin
160948	AP French Language
160949	AP French Literature
160950	AP Spanish Language
160951	AP Spanish Literature
160952	IB Latin
161000	Native American Languages, Other
161100	Semitic Languages, Other
161111	Hebrew 1
161112	Hebrew 2
161113	Hebrew 3
161114	Hebrew 4
161115	Arabic 1
161116	Arabic 2
161117	Arabic 3
161118	Arabic 4
161119	Foreign Language Contract – Arabic Independent Study
161200	Indo-European Languages, Other
161211	Turkish 1
161212	Turkish 2
161300	Non-English Languages for Native Speaker, Other
161311	Spanish for Native Speakers 1
161312	Spanish for Native Speakers 2
161313	Spanish for Native Speakers 3
161314	Spanish for Native Speakers 4
161315	Spanish for Native Speakers 5/Advanced Placement
161321	Portuguese for Native Speakers 1
161322	Portuguese for Native Speakers 2
161323	Portuguese for Native Speakers 3
161324	Portuguese for Native Speakers 4
161331	Italian for Native Speakers 1
161332	Italian for Native Speakers 2
161333	Italian for Native Speakers 3
161341	Japanese for Native Speakers 1
161342	Japanese for Native Speakers 2
161343	Japanese for Native Speakers 3
161351	Chinese for Native Speakers 1
161352	Chinese for Native Speakers 2
161353	Chinese for Native Speakers 3
161361	French for Native Speakers 1
161362	French for Native Speakers 2
161363	French for Native Speakers 3
161364	French for Native Speakers 4
169900	Foreign Languages, Other

Career and Technical Education Courses

The career and technical education curriculum contains 10 subject areas: agriculture and natural resource; science, technology, engineering, and mathematics; architecture and construction; business; computer and information sciences; health sciences; manufacturing, repair, and transportation; communications and design; personal services and culinary arts; and public services. Courses within each subject area along with their CSSC code is listed below.

Agriculture and Natural Resource

CSSC Code	Course Title
000101	Agricultural Business and Management, Other
010111	Agribusiness, Introduction; Agricultural Business
010121	Agricultural Business Operation; Agricultural Business Leadership
010131	Farm and Ranch Management
010141	State and Community Agriculture
010161	Agricultural Microprocessing
010171	Agriculture Cooperatives; Agricultural Cooperative Education I
010172	Agricultural Cooperative Education II
010181	Agriculture, Independent Study
010182	SOEP—Supervised Occupational Experience Program
000102	Agricultural Mechanics, Other
010211	Agricultural Mechanics, General; Agricultural Construction and Maintenance
010212	Agricultural Mechanics 2
010213	Agricultural Mechanics 3
010214	Agricultural Mechanics 4
010221	Welding, Agricultural
010231	Power and Machinery, Agricultural; Small Engines, Agricultural
010241	Farm Construction
010251	Electricity and Electronics, Agricultural
010261	Soil and Water Mechanical Practices
010271	Surveying, Agricultural
000103	Agricultural Production, Other
010311	Agricultural Production, General; Production Agriculture
010312	Agriculture Technology 1
010313	Agriculture Technology 2
010321	Animal and Veterinary Science; Animal Husbandry; Animal Production
010331	Crop Production
000104	Agricultural Products and Processing, Other
010411	Agricultural Products and Processing I
010412	Agricultural Products and Processing II
010421	Agricultural Products and Processing—Cooperative Education
000105	Agricultural Services and Supplies, Other
010511	Agricultural Supplies Marketing
000106	Horticulture, Other
010611	Horticulture; Plant Propagation
010621	Floriculture; Floriculture and Gardening
010631	Landscaping; Landscaping and Home Fruit Production; Landscape Maintenance and Construction; Landscape Design
010632	Landscaping, Advanced
010641	Greenhouse Management
010651	Nursery Operations and Management; Nursery Practices; Nursery Management
010661	Horticulture Mechanics I; Horticulture Power Equipment Operation and Maintenance
010662	Horticulture Mechanics II; Horticulture Mechanics—Cooperative Education
010671	Turf Management
010681	Fruit and Vegetable Production
000107	International Agriculture, Other
000199	Agribusiness and Agricultural Production, Other
000201	Agricultural Sciences, Other General
020111	Agricultural Sciences, General; Agriculture Fundamentals
020121	Agricultural Occupations 1
020122	Agricultural Occupations 2
020123	Agricultural Occupations 3
020124	Agricultural Occupations 4
000202	Animal Sciences, Other
020211	Animal Sciences 1
020212	Animal Sciences 2
020221	Livestock 9
020222	Livestock 10
020231	Poultry
020241	Dairy Production

020251	Nutrition and Feeds
020261	Horse Production
020262	Horseshoeing/Farrier Training
020271	Small Animal Production
020272	Small Animal Production 2; Small Animal Production—Cooperative Education
020281	Fish Production
000203	Food Sciences, Other
000204	Plant Sciences, Other
020411	Agronomy; Plant Science
020421	Ornamental Horticulture 1
020422	Ornamental Horticulture 2
020423	Ornamental Horticulture 3
000205	Soil Sciences, Other
020511	Soil Sciences, General
000299	Agricultural Sciences, Other
000301	Renewable Natural Resources, Other General
000302	Conservation and Regulation, Other
030211	Conservation and Regulation; Soils, Forestry and Wildlife
030212	Environmental Management 1
030213	Environmental Management 2
030221	Environmental Management—Cooperative Education
000303	Fishing and Fisheries, Other
030311	Waterman Occupations
000304	Forestry Production and Processing, Other
000305	Forestry and Related Sciences, Other
030511	Forestry Science 1; Forestry, Introduction
030512	Forestry Science 2
030521	Forestry Occupations—Work Experience; Forestry—Cooperative Education
000306	Wildlife Management, Other
030611	Wildlife Management
030621	Rural Recreation
030711	Marine Management/Oceanography 1; Marine Technology 1
030712	Marine Management/Oceanography 2; Marine Technology 2
000399	Renewable Natural Resources, Other
004804	Precision Food Production, Other
551011	General Agriculture 1
551019	General Agriculture 1, not for credit
551021	General Agriculture 2
551029	General Agriculture 2, not for credit
551031	General Agriculture 3
551039	General Agriculture 3, not for credit
551111	Animal Care 1
551119	Animal Care 1, not for credit
551121	Animal Care 2
551129	Animal Care 2, not for credit
551211	Plant Care 1
551219	Plant Care 1, not for credit
551221	Plant Care 2
551229	Plant Care 2, not for credit
551311	Agricultural Mechanics 1
551319	Agricultural Mechanics 1, not for credit
551321	Agricultural Mechanics 2
551329	Agricultural Mechanics 2, not for credit
551411	Agricultural Work Study
551419	Agricultural Work Study, not for credit
551511	Agricultural Work Experience
551519	Agricultural Work Experience, not for credit

Science, Technology, Engineering, and Mathematics (OE/STEM)

CSSC Code	Course Title
150100	Architectural Technologies, Other
150111	Structural Engineering Technician
150200	Civil Technologies, Other
150211	Surveying
150221	Civil Engineering Technician

150300	Electrical and Electronic Technologies, Other
150311	Audio Electronics
150321	Electrical Technology
150331	Electronic Technology 1
150332	Electronic Technology 2
150333	Electronics Fabrication
150341	Electrical/Electronics Engineering Technician
150400	Electromechanical Instrumentation and Maintenance Technologies, Other
150411	Electromechanical Technology 1; Robotics Technology
150412	Electromechanical Technology 2
150421	Instrumentation Technology
150431	Computer-Assisted Design/Drafting (CAD)
150500	Environmental Control Technologies, Other
150511	Environmental Control Technologies
150600	Industrial Production Technologies, Other
150601	Industrial Research & Development; Product Creation/Improvement
150611	Industrial Production Technology 1; Manufacturing Process Technology 1
150612	Industrial Production Technology 2; Manufacturing Process Technology 2
150621	Chemical Manufacturing Technology
150631	Optics Technology
150700	Quality Control and Safety Technologies, Other
150711	Quality Control Technology
150800	Mechanical and Related Technologies, Other
150811	Automotive Design & Technology
150821	Mechanical Engineering Technology
150900	Mining and Petroleum Technologies, Other
150911	Mining Technology
150921	Petroleum Technology
159900	Engineering and Engineering-Related Technologies, Other
300300	Engineering and Other Disciplines, Other
300311	Engineering Concepts
401011	Aerospace Science
410100	Biological Technologies, Other
410200	Nuclear Technologies, Other
410300	Physical Science Technologies, Other
419900	Science Technologies, Other
480100	Drafting, Other
480111	Drafting 1; Mechanical Drawing 1; Projection Theory; Drafting Fundamentals
480112	Drafting 2; Mechanical Drawing 2; Projection, Applied; Drafting, Technical
480113	Drafting 3; Mechanical Drawing 3; Machine Drawing; Illustration, Technical
480114	Drafting 4; Mechanical Drawing 4
480131	Engineering Drawing 1; Engineering Drafting; Engineering Graphics 1
480132	Engineering Drawing 2; Engineering Graphics 2
480141	Blueprint Reading; Sketching and Blueprint Reading
480151	Drafting 1, Cooperative
480152	Drafting 2, Cooperative

Architecture and Construction

CSSC Code	Course Title
000401	Architecture and Environmental Design, Other General
000402	Architecture, Other
040211	Architecture, Introduction
040212	Architecture, Advanced
040221	Architectural Theory
000403	City, Community, and Regional Planning, Other
000404	Environmental Design, Other
000406	Landscape Architecture, Other
000407	Urban Design, Other
000499	Architecture and Environmental Design, Other

480121	Architectural Drawing 1; Architectural Drafting
480122	Architectural Drawing 2
480123	Architectural Drawing 3
480124	Architectural Drawing 4; Architectural Model Building
210113	Electricity 1; Electrical Trades; Electricity, Basic
210114	Electricity 2; Electrical Trades, Advanced; Electrical Wiring Practices
021013	Electricity—Cooperative Education 1
210131	Electricity—Cooperative Education 2
004601	Brickmasonry, Stonemasonry, and Tile Setting, Other
460111	Bricklaying and Masonry 1; Masonry 1
460112	Bricklaying and Masonry 2; Masonry 2; Masonry, Advanced
460113	Masonry 3
460121	Tile Setting and Plastering
460131	Concrete Technician
004602	Carpentry, Other
460211	Carpentry 1
460212	Carpentry 2; Structural Woods; Carpentry, Advanced
460213	Carpentry 3
460311	Housewiring 1; Residential Wiring
460312	Housewiring 2
004604	Miscellaneous Construction Trades, Other
460411	Building Construction 1; House Construction; Building Trades 1; Home Mechanics; Manufactured Housing Assembly 1
460412	Building Construction 2; Building Trades 2; Manufactured Housing Assembly 2
460413	Building Construction 3; Building Trades 3; Manufactured Housing Assembly 3
460421	Painting and Decorating
460422	Flooring Installation
460431	Building Maintenance
460451	Building Construction—Cooperative Education 1; Construction Trades—Cooperative Education 1
460452	Building Construction—Cooperative Education 2; Construction Trades—Cooperative Education 2
004605	Plumbing, Pipefitting, and Steamfitting, Other
460511	Plumbing 1
460512	Plumbing 2
004699	Construction Trades, Other
558011	General Construction Trades 1
558019	General Construction Trades 1, not for credit
558021	General Construction Trades 2
558029	General Construction Trades 2, not for credit
558031	General Construction Trades 3
558039	General Construction Trades 3, not for credit
558111	Brickmasonry, Stonemasonry, and Tile Setting 1
558119	Brickmasonry, Stonemasonry, and Tile Setting 1, not for credit
558121	Brickmasonry, Stonemasonry, and Tile Setting 2
558129	Brickmasonry, Stonemasonry, and Tile Setting 2, not for credit
558211	Carpentry 1
558219	Carpentry 1, not for credit
558221	Carpentry 2
558229	Carpentry 2, not for credit
558311	Plumbing 1
558319	Plumbing 1, not for credit
558321	Plumbing 2
558329	Plumbing 2, not for credit
558411	Construction Trades Work Study 1
558419	Construction Trades Work Study 1, not for credit
558421	Construction Trades Work Study 2
558429	Construction Trades Work Study 2, not for credit
558511	Construction Trades Work Experience 1
558519	Construction Trades Work Experience 1, not for credit
558521	Construction Trades Work Experience 2
558529	Construction Trades Work Experience 2, not for credit

Business

CSSC Code	Course Title
070151	Recordkeeping 1; Recordkeeping, Clerical
070152	Recordkeeping 2; Recordkeeping Techniques, Specialized
070161	Office Machines; Business Machines; Adding and Calculating Machines
070162	Office Machines, Vocational
000703	Business Data Processing and Related Programs, Other
070311	Computers In Business; Business Computer Concepts
070321	Business Data Processing 1
070322	Business Data Processing 2
070331	Business Computer Programming 1; Business Computer Applications
070332	Business Computer Programming 2
070341	Keypunch Operator
070351	Data Entry Operator 1; Computer Operator
070352	Data Entry Operator 2
070371	Peripheral Computer Operator
000706	Secretarial and Related Programs, Other
070611	Shorthand 1; Stenography 1; Shorthand, Beginning
070612	Shorthand 2; Stenography 2; Shorthand, Advanced; Stenography, Advanced
070621	Transcription; Dictation and Transcription; Transcription, Machine; Touch Shorthand; Machine Shorthand
070631	Secretarial Administration 1; Secretarial Practice; Secretarial Procedures; Secretarial Office Practice; Secretarial Typewriting, Integrated; Secretarial Skills, Integrated
070632	Secretarial Administration 2
070641	Word Processing 1
070642	Word Processing 2
070643	Word Processing 3; Advanced Word Processing Applications
070651	Reprographics
070661	Legal Office Procedures; Legal Secretary
070671	Medical Office Procedures; Medical Office Assisting; Medical Secretary
070681	Legal/Medical Office Procedures
000707	Typing, General Office, and Related Programs, Other
070712	Typewriting 2; Typewriting, Advanced
070713	Typewriting 3; Typewriting, Executive; Typewriting, Career
070731	Office Procedures 1; Office Practice 1; Office Specialist 1; Automated Office 1; Office Skills, Integrated; Clerk Typist; Office Technology 1; Business Careers 1; Office Services 1; Clerk Typist 1
070732	Office Procedures 2; Office Practice 2; Office Career Occupations; Automated Office 2; Office Careers 2; Office Technology 2; Office Specialist 2; Clerk Typist 2; Business Careers 2
070733	Simulated Office; Model Office; Office Practice, Advanced; Business Experience, Simulated; Business Careers 3; Office Pool; Office Services, Advanced
070741	Office Education 1, Cooperative; Clerical On The Job Training; Office Training, Vocational; Office Occupations Work Experience
070742	Office Education 2, Cooperative
000799	Business and Office, Other
080781	Telephone Service Representative
080782	Telephone Directory Assistant
552011	General Office Practice 1
552019	General Office Practice 1, not for credit
552021	General Office Practice 2
552031	General Office Practice 3
552111	Office Machines 1
552121	Office Machines 2
552211	Business Work Study 1
552221	Business Work Study 2
552311	Business Work Experience 1
552321	Business Work Experience 2
060712	Hotel and Motel Training
000617	Real Estate, Other

061711	Real Estate Marketing
000801	Apparel and Accessories Marketing, Other
080111	Fashion Merchandising
080131	Fashion Merchandising—Cooperative Education 1
080132	Fashion Merchandising—Cooperative Education 2
000802	Business and Personal Services Marketing, Other
000804	Financial Services Marketing, Other
000805	Floristry, Farm and Garden Supplies Marketing, Other
080511	Floral Sales
000806	Food Marketing, Other
080611	Food Marketing/Distribution—Overview
080612	Grocery Management; Wholesale/Retail Grocery Operation
080621	Food Marketing—Cooperative Education 1
080622	Food Marketing—Cooperative Education 2
000807	General Marketing, Other
080711	Distributive Education 1; Sales and Marketing; Retailing and Merchandising; Distribution and Marketing; Distribution 1; Marketing and Distribution 1; Merchandising
080712	Distributive Education 2; Distribution 2; Marketing and Distribution 2
080713	Distributive Education 3
080721	Distributive Education 1, Cooperative; Store Experience; Marketing Occupational Experience
080722	Distributive Education 2, Cooperative
080731	Salesmanship
080741	Retail Learning Laboratory
080751	Cashier Checker Training
080771	Distributive Education, Independent Study
000808	Home and Office Products Marketing, Other
080811	Computer Sales Representative
000809	Hospitality and Recreation Marketing, Other
080911	Orientation to Hospitality Careers
080921	Hospitality Sales 1
080922	Hospitality Sales 2
000081	Insurance Marketing, Other
000811	Transportation and Travel Marketing, Other
000812	Vehicles and Petroleum Marketing, Other
081211	Auto Parts Merchandising
081221	Automotive Service Station Operation; Automotive Professional Training
000899	Marketing and Distribution, Other
000601	Business and Management, Other General
060111	Business Introduction; Business, General; Business Survey; Business, Basic; Business Dynamics; Business Careers Overview
060121	Business Law
060131	Business, Independent Study
060141	Business Education, Cooperative
000604	Business Administration and Management, Other
060411	Business Organization and Management; Business Management; Business Leadership; Junior Executive Training
000605	Business Economics, Other
060511	Business Economics
000606	Human Resources Development, Other
000607	Institutional Management, Other
060711	Hotel and Motel Management
000609	International Business Management, Other
000611	Labor Industrial Relations, Other
000612	Management Information Systems, Other
000613	Management Science, Other
000614	Marketing Management and Research, Other
061411	Marketing Management and Decision Making; Marketing Studies; Merchandising and Sales Management
000615	Organizational Behavior, Other
000616	Personnel Management, Other
000618	Small Business Management and Ownership, Other
061811	Small Business Management

000062	Trade and Industrial Supervision and Management, Other
000699	Business and Management, Other
000704	Office Supervision and Management, Other
000705	Personnel and Training Programs, Other
000803	Entrepreneurship, Other
080311	Starting Your Own Business
080321	Junior Achievement; Student-Operated Company
000602	Accounting, Other
060211	Accounting/Business Management Careers—Integrated Curriculum
000603	Banking and Finance, Other
060311	Financial Careers
060321	Real Estate Finance
060331	Consumer Lending
000608	Insurance and Risk Management, Other
060811	Insurance Careers
000061	Investments and Securities, Other
061011	Investments and Taxation
000619	Taxation, Other
000701	Accounting, Bookkeeping, and Related Programs, Other
070111	Bookkeeping 1; Bookkeeping, Beginning
070112	Bookkeeping 2; Bookkeeping, Advanced
070121	Accounting 1; Clerical Accounting 1
070122	Accounting 2; Accounting, Advanced; Accounting Careers; Clerical Accounting 2
070131	Accounting, College
070141	Bookkeeping and Accounting 1
070142	Bookkeeping and Accounting 2
000702	Banking and Related Financial Programs, Other
070201	Banking and Financial Careers
070211	Bank Teller
070231	Bank Proof Operator
070241	Bank Data Entry Occupations
070251	Banking and Financial Careers—Cooperative Education

Computer and Information Sciences

CSSC Code	Course Title
001101	Computer and Information Sciences, Other General
110121	Computer Mathematics 1; Computer Problem Solving; Mathematics and Computing
110122	Computer Mathematics 2
110131	Computer Applications; Computer Sciences 1
110132	Computer Applications, Independent Study; Computer Sciences 2
110141	Computer Science, Advanced Placement; Computer Sciences 3
110143	AP Computer Science A
110144	AP Computer Science AB
110151	Artificial Intelligence
001102	Computer Programming, Other
110211	Computer Programming 1
110212	Computer Programming 2
110213	Computer Programming 3
110221	FORTRAN, Introduction
110231	PASCAL, Introduction; PASCAL 1
110232	Advanced PASCAL; PASCAL 2
110241	BASIC, Introduction; BASIC 1
110242	Advanced BASIC; BASIC 2
110251	COBOL, Introduction; COBOL 1
110252	Advanced COBOL; COBOL 2
110261	LOGO, Introduction
110271	RPG Programming, Introduction
110272	C Programming
110273	C++ Programming
001103	Data Processing, Other
110311	Data Processing, Introduction; Data Processing Systems and Procedures; Computer Concepts; Data Processing; Electronic Data Processing; Data Systems 1
110312	Data Processing, Intermediate; Data Processing 2
110313	Data Processing, Advanced; Data Processing, Internship
110321	Computer Programming—Cooperative Education
001104	Information Sciences and Systems, Other
001105	Systems Analysis, Other
001106	Computer Programming and Website Design, Other
110601	HTML
110602	Java, Java Script
110603	Web Site Design, Development
110604	Network Administration/Management
001199	Computer and Information Sciences, Other

Health Sciences

CSSC Code	Course Title
001701	Dental Services, Other
170111	Dental Assistant 1; Dental Office Assisting
170112	Dental Assistant 2
170121	Dental Assistant, Cooperative
170131	Dental Technology 1
170132	Dental Technology 2
001702	Diagnostic and Treatment Services, Other
170211	First Aid; CPR and First Aid; Medical Emergencies; Emergency Medical Technician
170221	EKG Technician
001703	Medical Laboratory Technologies Other
170311	Laboratory Program 1; Health Technology
170312	Laboratory Program 2
170321	Chemical Technology 1; Chemistry Lab; Chemistry, Qualitative

170322	Chemical Technology 2
001704	Mental Health/Human Services, Other
170411	Home Health Aide
170421	Community Health
170431	Mental Health Worker; Psychiatric Aide
001705	Miscellaneous Allied Health Services, Other
170511	Health Occupations 1; Health Careers; Medical Career Opportunities
170521	Health Occupations 2; Health Occupations Training Medical Careers Work Experience
170522	Central Service Technician
170531	Medical Terminology
170541	Medical Records Secretary
170551	Medical Assisting
170561	Sports Medicine
170571	Veterinary Science; Veterinary Aide
170591	Health Occupations, Independent Study
170592	Health Occupations—Cooperative Education 1
170593	Health Occupations—Cooperative Education 2
001706	Nursing-Related Services, Other
170611	Health Office; Student Assessment of Child Health
170621	Nursing, Introduction; Nursing, Practical
170631	Nurse Aide and Orderly; Nurse's Assistant; Patient Care Technician
170641	Nurse Aide, Cooperative
001707	Ophthalmic Services, Other
170711	Optical Services Assistant
001708	Rehabilitation Services, Other
001799	Allied Health, Other
001801	Audiology and Speech Pathology, Other
001802	Basic Clinical Health Sciences, Other
001803	Chiropractic, Other
001804	Dentistry, Other
001805	Emergency/Disaster Science, Other
001806	Epidemiology, Other
001807	Health Sciences Administration
001808	Hematology, Other
001809	Medical Laboratory, Other
000181	Medicine, Other
001811	Nursing, Other
001812	Optometry, Other
001813	Osteopathic Medicine, Other
001814	Pharmacy, Other
181411	Pharmacy Technician
001815	Podiatry, Other
001816	Population and Family Planning, Other
001817	Pre-Dentistry, Other
001818	Pre-Medicine, Other
181801	Medical Ethics
001819	Pre-Pharmacy, Other
000182	Pre-Veterinary, Other
001822	Public Health Laboratory Science, Other
001823	Toxicology (Clinical), Other
001824	Veterinary Medicine, Other
001899	Health Sciences, Other
200461	Dietetic Aide
310121	Search & Rescue
553011	General Health Occupations 1
553019	General Health Occupations 1, not for credit
553021	General Health Occupations 2
553029	General Health Occupations 2, not for credit
553031	General Health Occupations 3
553039	General Health Occupations 3, not for credit
553111	Health Occupations Work Study 1
553119	Health Occupations Work Study 1, not for credit
553121	Health Occupations Work Study 2
553129	Health Occupations Work Study 2, not for credit
553211	Health Occupations Work Experience 1
553219	Health Occupations Work Experience 1, not for credit
553221	Health Occupations Work Experience 2
553229	Health Occupations Work Experience 2, not for credit

Manufacturing, Repair, and Transportation

CSSC Code	Course Title
200131	Clothing 7
200132	Clothing 8
200133	Clothing 1; Sewing, Introduction; Sewing 1; Textiles and Clothing 1; Clothing Construction
200134	Clothing 2; Sewing, Intermediate; Sewing 2; Textiles and Clothing 2; Clothing Construction, Intermediate
200135	Clothing 3; Sewing 3; Textiles and Clothing 3
200136	Clothing 4; Sports Wear; Alterations
200137	Tailoring
002003	Clothing, Apparel, and Textiles Management, Production, and Services, Other
200311	Clothing Occupations 1; Fashion Design and Clothing Occupations; Profitable Sewing 1
200312	Clothing Occupations 2; Profitable Sewing 2
200313	Clothing Occupations 3
200314	Clothing Occupations—Cooperative Education 1
200315	Clothing Occupations—Cooperative Education 2
200331	Commercial Garment and Apparel Construction
200341	Custom Apparel Construction
200351	Custom Tailoring and Alteration
200381	Textiles Testing
200391	Clothing Production Management
200551	Custom Drapery and Window Treatment Design
200561	Custom Slipcovering and Upholstering
210115	Electronics 1; Electronics, Basic; Circuits, Fundamental
210116	Electronics 2; Electronics, Digital
210117	Electronics 3
210118	Electronics 4
210119	Electricity and Electronics, Introduction
021012	Electricity and Electronics, Advanced
210121	Machine Shop 1; Machine Lab; Industrial Machine
210122	Machine Shop 2
210123	Machine Shop 3
210124	Machine Shop 4
021014	Electronics—Cooperative Education 1
210141	Electronics—Cooperative Education 2
021015	Electricity/Electronics—Cooperative Education 1
210151	Electricity/Electronics—Cooperative Education 2
470161	Industrial Electricity
470171	Industrial Electronics
470431	Shoe Repair and Orthopedics 1
470432	Shoe Repair and Orthopedics 2
004803	Leatherworking and Upholstering, Other
480311	Leatherwork 1
480312	Leatherwork 2
480321	Upholstery
480322	Upholstery, Advanced
480331	Auto Upholstery
004805	Precision Metal Work, Other
480511	Metal 1; Metal Class; Metal Lab; Metalwork; Metal Trades; Machine Metals
480512	Metal 2; Metalwork, Advanced
480513	Metal 3
480514	Metal 4
480521	Welding 1
480522	Welding 2
480523	Welding 3
480524	Welding—Cooperative Education
480531	Sheet Metal 1
480532	Sheet Metal 2
480541	Metal Restoration
480551	Foundry 1
480552	Foundry 2
004806	Precision Work, Assorted Materials, Other
480611	Plastics 1

480612	Plastics 2
480621	Spaceage Plastics
004807	Woodworking, Other
480711	Woodworking 1; Wood 1; Woodworking, Basic
480712	Woodworking 2; Wood 2; Machine Woodworking; Wood Products
480713	Woodworking 3; Wood 3; Woodworking, Advanced
480714	Woodworking 4; Wood 4
480721	Furniture Refinishing
480731	Cabinetmaking 1; Millwork
480732	Cabinetmaking 2
004899	Precision Production, Other
490121	Aviation Technology 1; Aviation, General; Avionics Technology
490122	Aviation Technology 2
490123	Aviation Technology 3
490124	Aviation Technology 4
490321	Boat Building
520107	Adaptive Foundry EMH
554211	Clothing and Textiles 1
554219	Clothing and Textiles 1, not for credit
554221	Clothing and Textiles 2
554229	Clothing and Textiles 2, not for credit
557211	Leatherwork and Upholstery 1
557219	Leatherwork and Upholstery 1, not for credit
557221	Leatherwork and Upholstery 2
557229	Leatherwork and Upholstery 2, not for credit
557411	Precision Production Work Study 1
557419	Precision Production Work Study 1, not for credit
557421	Precision Production Work Study 2
557429	Precision Production Work Study 2, not for credit
557511	Precision Production Work Experience 1
557519	Precision Production Work Experience 1, not for credit
557521	Precision Production Work Experience 2
557529	Precision Production Work Experience 2, not for credit
120511	General Services Occupations 1
120512	General Services Occupations 2
120513	General Services Occupations 3
120514	General Services Occupations 4
120521	Building & Grounds Maintenance Occ 1
120522	Building & Grounds Maintenance Occ 2
120523	Building & Grounds Maintenance Occ 3
120531	Industrial Maintenance/Mechanics 1
120532	Industrial Maintenance/Mechanics 2
004603	Electrical and Power Transmission Installation, Other
460321	Electric Power and Communications Lineworker
004701	Electrical and Electronic Equipment Repair, Other
470111	Small Appliance Repair
470121	Radio and TV Repair 1; Television Repair; Electronic Servicing
470122	Radio and TV Repair 2
470123	Radio and TV Repair 3
470124	Telecommunications Technician
470131	Appliance Repair 1; Major Appliance Repair
470132	Appliance Repair 2; Appliance Repair, Advanced
470141	Vending Machine Repair
470151	Business Machine Repair; Office Machine Repair
470181	Food Processing Machine Maintenance Technician/Repair
004702	Heating, Air Conditioning, and Refrigeration Mechanics, Other
470211	Air Conditioning, Refrigeration, and Heating; Refrigeration and Air Conditioning 1; Commercial Heating and Air Conditioning
470212	Air Conditioning, Refrigeration, and Heating, Advanced; Refrigeration and Air Conditioning 2
470213	Air Conditioning, Refrigeration, and Heating 3
004703	Industrial Equipment Maintenance and Repair, Other
470311	Industrial Mechanics 1; Heavy Equipment Mechanics; Industrial Equipment Mechanics
470312	Industrial Mechanics 2
470321	Diesel Mechanics

470331	Industrial Maintenance Mechanics 1
470332	Industrial Maintenance Mechanics 2
470341	Petroleum Drilling Equipment Operation and Maintenance 1
470342	Petroleum Drilling Equipment Operation and Maintenance 2
470343	Petroleum Drilling Equipment Operation and Maintenance 3
004704	Miscellaneous Mechanics and Repairers, Other
470411	Musical Instrument Repair
470421	Instrument Maintenance and Repair
470433	Watch and Clock Repair
470434	Bicycle Repair
004705	Stationary Energy Sources, Other
470511	Power Mechanics 1; Power Conversion 1; Power Technology 1; Energy and Transportation 1
470512	Power Mechanics 2; Power Technology 2; Energy and Transportation 2
470513	Power Mechanics 3
470514	Power Mechanics 4
470521	Hydraulics and Pneumatics
004706	Vehicle and Mobile Equipment Mechanics and Repairers, Other
470611	Small Engine Repair 1; Small Engine Maintenance; Mechanics Trades; Small Gas Maintenance; Motorcycle and Recreational Vehicle Repair
470612	Small Engine Repair 2; Mechanics Trades, Advanced
470621	Auto Mechanics 1; Auto Repair; Auto Engines; Vehicle Power
470622	Auto Mechanics 2; Automotive Technology; Auto Tuneup
470623	Auto Mechanics 3; Auto Mechanics, Advanced
470624	Auto Mechanics—Cooperative Education 1
470625	Auto Mechanics—Cooperative Education 2
470631	Auto Body 1; Auto Body and Fender; Auto Body Repair; Body and Fender
470632	Auto Body 2; Auto Body Repair, Advanced
470633	Auto Body 3
470641	Auto Service 1; Auto Maintenance
470642	Auto Service 2
470661	Airframes 1
470662	Airframes 2
470671	Aviation Powerplant 1
470672	Aviation Powerplant 2
470673	Aviation Powerplant 3
470674	Aviation Powerplant 4
470681	Aviation Quality Control 1
470682	Aviation Quality Control 2
470691	Aircraft Sheetmetal 1
470692	Aircraft Sheetmetal 2
004799	Mechanics and Repairers, Other
490141	Aircraft Parts Management 1
490142	Aircraft Parts Management 2
490311	Marine Engine and Boat Repair 1; Marine Mechanics, Basic
490312	Marine Engine and Boat Repair 2; Marine Mechanics, Advanced
490341	Aquatic Occupations; Marine Diving
559011	Auto Service 1
559019	Auto Service 1, not for credit
559021	Auto Service 2
559029	Auto Service 2, not for credit
559111	Auto Service Work Experience 1
559119	Auto Service Work Experience 2, not for credit
559121	Auto Service Work Experience 2
559129	Auto Service Work Experience 2, not for credit
080761	Warehousing Industrial and Wholesale Material Handling
004901	Air Transportation, Other
490111	Aeronautics 1; Aerospace for Today
490112	Aeronautics 2
004902	Vehicle and Equipment Operation, Other
490211	Forklift Operator
490212	Tractor-Trailer Truck Driving
490213	Heavy Vehicle Operation/Earth Moving Equipment
490214	Bus Driver/Chauffeur
004903	Water Transportation, Other
490331	Navigation

490411	Transportation Technology 1; Introduction to Transportation Industry
490412	Transportation Technology 2
490421	Transportation/Traffic Technician
004999	Transportation and Material Moving, Other

Communications and Design

CSSC Code	Course Title
000405	Interior Design, Other
040511	Interior Design
080121	Fashion Design and Illustration
000901	Communications, Other General
090111	Mass Media; Channels of Communications; Media Communications; Media and Persuasion; Media in Society; Media and Critical Thinking
090121	Intercultural Communications
000902	Advertising, Other
090211	Advertising
000903	Communications Research, Other
090441	Yearbook Production 1; Publications 1
090442	Yearbook Production 2; Publications 2
000905	Public Relations
000906	Radio/Television News Broadcast, Other
090611	Broadcast Journalism; Television News
090612	Careers in Radio/Television Broadcasting
000907	Radio/Television, Other General
090711	Broadcasting, Introduction
090721	Radio and Television Appreciation; Television and Taste
000999	Communications, Other
001001	Communication Technologies, Other
100111	World of Communications
100121	Audio Visuals; Media Production Aide; Communications Media Production
100131	Photography, Commercial; Photojournalism
100132	Advanced Commercial Photography
100141	Broadcast Management 1
100142	Broadcast Management 2
100143	Broadcasting Practicum
100151	Film Making and Production 1; Cinematography; Filming and Staging; Film Technology
100152	Film Making and Production 2
100161	Radio Production
100171	Telecommunications 1; Television Occupations; Television Production 1; Videotape Production
100172	Television Production 2
100173	Television Production 3
100174	Television Production 4
100181	Cable Television
100191	Radio/Television Production 1
100192	Radio/Television Production 2
200511	Housing and Interior Design 1; Homes and Interiors; Home Furnishings; Living Environments
200512	Housing and Interior Design 2
200513	Interior Design Occupations; Home Environment Occupations
200521	Floral Design
200531	Home Decorating
004802	Graphic and Printing Communications, Other
480211	Commercial Art 1; Advertising Design
480212	Commercial Art 2; Advertising and Illustration, Advanced
480213	Commercial Art, Cooperative
480214	Commercial Art 3; Advanced Commercial Art
480221	Graphic Arts 1; Printing, Introduction; Production Printing; Graphic Communications 1
480222	Graphic Arts 2; Printing, Advanced; Graphic Communications 2
480223	Graphic Arts 3; Printing Production—Cooperative
480224	Graphic Arts 4
480231	Sign Painting 1; Lettering

480232	Sign Painting 2
480233	Sign Painting 3
480241	Bindery
480251	Electronic Composition
480261	Copy Editing
480271	Desktop Publishing
005004	Design, Other
500411	Graphic Design
005008	Graphic Arts Technology, Other
500811	Computer Graphics Design; Computer Art
557111	Graphic and Printing Communications 1
557119	Graphic and Printing Communications 1, not for credit
557121	Graphic and Printing Communications 2
557129	Graphic and Printing Communications 2, not for credit

Personal Services and Culinary Arts

CSSC Code	Course Title
010521	Animal Grooming; Pet Grooming
081111	Tourism Services
081121	Entertainment Park/Tourism—Cooperative Education
001201	Drycleaning and Laundering Services, Other
120111	Dry Cleaning 1
120112	Dry Cleaning 2
001202	Entertainment Services, Other
001203	Funeral Services, Other
001204	Personal Services, Other
120411	Cosmetology; Care of the Nails and Skin; Esthetician; Creative Coiffure and Shaping and Conditioning Hair
120412	Cosmetology 2; Cosmetology, Advanced; Wigology and the Professional Business of Cosmetology
120413	Cosmetology 3
120414	Cosmetology – Cooperative Educ. 2 (1?)
120415	Cosmetology – Cooperative Educ. 2
120421	Barbering 1
120422	Barbering 2
120423	Barbering 3
120431	Personal Services Occupations
001299	Consumer, Personal, and Miscellaneous Services, Other
001903	Family and Community Services, Other
200121	Child Development 8
200122	Child Development 1
200123	Child Development 2
200124	Child Development 3
200125	Child Development 4
200126	Current Issues in Child Development
200151	Home Economics Occupations 1, Exploratory; Home Economics Job Training Exploration
200152	Home Economics Occupations 2, Exploratory
200153	Home Economics Laboratory Assistant
200154	Home Economics Leadership
200161	Family Health 1; Family Nursing
200162	Family Health 2; Family Nursing, Advanced
200193	Home Economics—Cooperative Education 1
200194	Home Economics—Cooperative Education 2
002002	Child Care and Guidance Management and Services, Other
200211	Child Care Services; Early Childhood Workshop; Child Development Services; Nursery School Training
200221	Child Care Aide
200231	Child Care Management
200241	Family Care Services; Foster Care and Family Care
200261	Child Care—Cooperative Education 1
200262	Child Care—Cooperative Education 2
200321	Clothing Maintenance Aide
200361	Wedding and Specialty Consulting
200371	Fashion and Fabric Coordination

002005	Home Furnishings and Equipment Management, Production, and Services, Other
200541	Home Furnishings Aide
200571	Home-Service Assisting 1
200572	Home-Service Assisting 2
200573	Home-Service Asst—Cooperative Education 1
200574	Home-Service Asst—Cooperative Education 2
002006	Institutional, Home Management, and Supporting Services, Other
200611	Custodial Services
200621	Executive Housekeeping
200631	Homemaker's Aide; Homemaker's Assistant, Home Management
200641	Geriatrics 1; Companion to the Aged
200642	Geriatrics 2
200643	Geriatrics—Cooperative Education 1
200644	Geriatrics—Cooperative Education 2
200651	Consumer Aide
200661	Therapeutic Recreation Aide
200671	Institutional, Home Management Support Services—Cooperative Education
002099	Vocational Home Economics, Other
003101	Parks and Recreation, Other General
310111	Recreation Aide
003102	Outdoor Recreation, Other
310211	Winter/Ski Resort Operation
003103	Parks and Recreation Management, Other
003104	Water Resources, Other
003199	Parks and Recreation, Other
490131	Air Travel Service Occupations
554111	Child Development 1
554119	Child Development 1, not for credit
554121	Child Development 2
554129	Child Development 2, not for credit
556111	Cosmetology/Barber 1
556119	Cosmetology/Barber 1, not for credit
556121	Cosmetology/Barber 2
556129	Cosmetology/Barber 2, not for credit
556211	Custodial and Housekeeping Services 1
556219	Custodial and Housekeeping Services 1, not for credit
556221	Custodial and Housekeeping Services 2
556229	Custodial and Housekeeping Services 2, not for credit
556411	Miscellaneous Services 1
556419	Miscellaneous Services 1, not for credit
556421	Miscellaneous Services 2
556429	Miscellaneous Services 2, not for credit
556511	Service Occupations Work Study 1
556519	Service Occupations Work Study 1, not for credit
556521	Service Occupations Work Study 2
556529	Service Occupations Work Study 2, not for credit
556611	Service Occupations Work Experience 1
556619	Service Occupations Work Experience 1, not for credit
556621	Service Occupations Work Experience 2
556629	Service Occupations Work Experience 2, not for credit
200188	Nutrition; Fitness Foods
002004	Food Production, Management, and Services, Other
200411	Food Service Training 1; Culinary Arts 1; Commercial Foods, Basic; Restaurant Occupations 1; Chef Class
200412	Food Service Training 2; Culinary Arts 2; Commercial Foods, Advanced; Restaurant Occupations 2
200413	Food Services/Restaurant Management
200421	Food Service Cooperative Training; Food Service, Vocational
200431	Baking
200441	Chef
200451	Catering
200471	Food Testing
200481	Cafeteria Assistant; School Food Service
480411	Meatcutting 1
480412	Meatcutting 2
520106	Adaptive Foods EMH
556311	Food Services 1
556319	Food Services 1, not for credit

556321	Food Services 2
556329	Food Services 2, not for credit
557311	Meatcutting 1
557319	Meatcutting 1, not for credit
557321	Meatcutting 2
557329	Meatcutting 2, not for credit

Public Services

CSSC Code	Course Title
001301	Education, Other General
001302	Bilingual/Bicultural Education, Other
001303	Curriculum and Instruction, Other
001304	Education Administration, Other
001305	Educational Media, Other
001306	Evaluation and Research, Other
001307	International and Comparative Education, Other
001308	School Psychology, Other
001309	Social Foundations, Other
000131	Special Education, Other
001311	Student Counseling and Personnel Services, Other
001312	Teacher Education, General Programs, Other
001313	Teacher Education, Specific Subject Areas, Other
001314	Teaching English as a Second Language/Foreign Language, Other
001399	Education, Other
200251	Teacher Aide/Elementary
200252	Teacher Aide/Secondary
002501	Library and Archival Sciences, Other General
250111	Library Science; Library Skills
002502	Archival Science, Other
002503	Library Assisting, Other
250311	Library Assistant; Library Aide
002504	Library Science, Other
002505	Museology, Other
002599	Library and Archival Sciences, Other
004401	Public Affairs, Other General
004402	Community Services, Other
004403	International Public Service, Other
004404	Public Administration, Other
004405	Public Policy Studies, Other
004406	Public Works, Other
004407	Social Work, Other
440711	Human Services
004499	Public Affairs, Other
070662	Court Reporter
001821	Prosecutorial Science, Other
004301	Criminal Justice, Other
430111	Law Enforcement; Police Science; Criminal Justice
430121	Law Science; Forensic Studies
004302	Fire Protection, Other
430211	Fire Fighting Practices; Fire Science
430221	Fire Safety Education
004303	Security Services, Other
430311	Security Guard
004399	Protective Services, Other
004504	Criminology, Other

Appendix C
Parameter Estimates for Control Variables from the Multivariate Regression Models

Table C-1. Fixed-effects estimates of the effect of total academic and occupational courses on math achievement

	Number-right score	Proficiency probability scores				
		Level 1	Level 2	Level 3	Level 4	Level 5
Total occupational courses	-0.089	-0.001	0.001	-0.000	-0.004	-0.001*
	(0.085)	(0.002)	(0.003)	(0.005)	(0.004)	(0.001)
Total academic courses	0.345**	-0.003**	-0.002	0.004**	0.015**	0.009**
	(0.033)	(0.001)	(0.002)	(0.000)	(0.001)	(0.001)
Spring 2003–04 school year	1.850**	0.059**	0.083**	0.086**	0.003	-0.042**
	(0.643)	(0.004)	(0.011)	(0.019)	(0.014)	(0.009)
Math homework	0.958**	-0.001	0.007	0.008	0.030**	0.021**
	(0.215)	(0.006)	0.011)	(0.007)	(0.004)	(0.001)
Missing	-0.974**	-0.019	-0.026	-0.029**	-0.023**	-0.005
	(0.277)	(0.016)	(0.015)	(0.008)	(0.003)	(0.003)
Extracurricular activities	0.098	0.001	-0.011	0.001	0.012	0.000
	(0.439)	(0.005)	(0.010)	(0.008)	(0.009)	(0.001)
Missing	1.090**	-0.036**	0.007	0.061**	0.056**	0.017
	(0.300)	(0.005)	(0.013)	(0.005)	(0.005)	(0.003)
Employment	-0.105	-0.004	0.002	0.004	-0.003	-0.002
	(0.355)	(0.009)	(0.013)	(0.015)	(0.003)	(0.001)
Missing	-0.092	-0.019	-0.013	0.014	-0.003	0.001
	(0.518)	(0.016)	(0.019)	(0.023)	(0.003)	(0.002)
Importance of education	-0.120	-0.000	-0.005	0.003	-0.001	-0.002
	(0.124)	(0.006)	(0.003)	(0.014)	(0.012)	(0.006)
Missing	0.238	-0.000	0.001	-0.001	0.013*	0.006**
	(0.601)	(0.007)	(0.027)	(0.025)	(0.006)	(0.002)
Expects college degree	0.985**	0.007	0.007	0.022	0.035**	0.007**
	(0.080)	(0.004)	(0.005)	(0.015)	(0.006)	(0.002)
Missing	-0.335	0.001	-0.004	-0.006	-0.010*	-0.008
	(0.380)	(0.011)	(0.015)	(0.004)	(0.025)	(0.006)
Constant	41.234**	0.968**	0.737**	0.445**	0.027	-0.099**
	(0.495)	(0.012)	(0.022)	(0.008)	(0.025)	(0.009)
Math efficacy scale	0.274	0.002	0.006	0.015*	0.005	-0.001
	(0.136)	(0.004)	(0.005)	(0.007)	(0.004)	(0.001)
Missing	0.083	-0.003	0.006	-0.010	0.011	0.006
	(0.223)	(0.005)	(0.005)	(0.011)	(0.011)	(0.004)
Parental investment scale	0.061	0.005	0.005	0.002	-0.004	-0.001
	(0.092)	(0.003)	(0.003)	(0.008)	(0.003)	(0.001)
Missing	0.093	-0.006	-0.006	0.020	0.005	0.002
	(0.506)	(0.015)	(0.013)	(0.033)	(0.008)	(0.007)

See notes at end of table.

Table C-1. Fixed-effects estimates of the effect of total academic and occupational courses on math achievement—continued

	Number-right score	Proficiency probability scores				
		Level 1	Level 2	Level 3	Level 4	Level 5
Held back a grade	-0.121	0.007	0.025	-0.034	-0.024	-0.004
	(1.113)	(0.016)	(0.042)	(0.073)	(0.019)	(0.007)
Constant	41.234**	0.968**	0.737**	0.445**	0.027	-0.099**
	(0.495)	(0.012)	(0.022)	(0.008)	(0.025)	(0.009)

NOTE: Numbers in parentheses are standard errors.
N = 7,160
* $p < 0.05$
** $p < 0.01$

Table C-2. Fixed-effects estimates of the effect of the percentage of courses that are occupational on math achievement

	Number-right score	Proficiency probability scores				
		Level 1	Level 2	Level 3	Level 4	Level 5
Percent occupational courses	-0.054**	0.001*	0.001	-0.000	-0.003**	-0.001**
	(0.015)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)
Spring 2003–04 school year	5.077**	0.025**	0.065**	0.120**	0.147**	0.045**
	(0.201)	(0.005)	(0.011)	(0.013)	(0.003)	(0.003)
Math homework	1.126**	-0.002	0.007	0.010	0.037**	0.026**
	(0.196)	(0.004)	(0.013)	(0.007)	(0.004)	(0.001)
Missing	-1.056	0.002	-0.026	-0.030**	-0.026**	-0.007*
	(0.272)	(0.002)	(0.018)	(0.009)	(0.004)	(0.003)
Extracurricular activities	0.151	0.000	-0.011	0.001	0.014	0.001
	(0.361)	(0.003)	(0.009)	(0.010)	(0.009)	(0.001)
Missing	1.324**	-0.039**	0.005	0.063**	0.067**	0.023**
	(0.291)	(0.004)	(0.013)	(0.008)	(0.007)	(0.004)
Employment	-0.053	-0.004	0.001	0.005	-0.000	-0.000
	(0.343)	(0.007)	(0.012)	(0.019)	(0.003)	(0.002)
Missing	-0.006	-0.020	-0.013	0.015	0.020**	0.003
	(0.473)	(0.012)	(0.021)	(0.032)	(0.004)	(0.002)
Importance of education	-0.174	0.000	-0.005*	0.002	-0.004	-0.004
	(0.130)	(0.005)	(0.003)	(0.014)	(0.013)	(0.005)
Missing	0.330	-0.001	0.001	-0.000	0.016**	0.009**
	(0.556)	(0.005)	(0.031)	(0.031)	(0.005)	(0.001)
Expects college degree	1.189**	0.005	0.006	0.024	0.044**	0.012**
	(0.061)	(0.003)	(0.005)	(0.018)	0.006)	(0.002)
Missing	-0.374	0.001	-0.004	-0.006	-0.012**	-0.009
	(0.319)	(0.007)	(0.015)	(0.006)	(0.003)	(0.005)
Constant	44.637**	0.932**	0.715**	0.480**	0.181**	-0.008
	(0.347)	(0.007)	(0.011)	(0.007)	(0.016)	(0.006)
Math efficacy scale	0.241	0.002	0.007	0.015*	0.004	-0.002
	(0.166)	(0.004)	(0.007)	(0.007)	(0.005)	(0.001)

See notes at end of table.

Table C-2. Fixed-effects estimates of the effect of the percentage of courses that are occupational on math achievement—continued

	Number-right score	Proficiency probability scores				
		Level 1	Level 2	Level 3	Level 4	Level 5
Missing	0.062	-0.003	-0.009	-0.010	0.010	0.006
	(0.179)	(0.005)	(0.005)	(0.010)	(0.013)	(0.005)
Parental investment scale	0.086	0.005	0.005	0.002	-0.003	-0.001
	(0.093)	(0.003)	(0.003)	(0.007)	(0.005)	(0.002)
Missing	0.091	-0.006	-0.006	0.020	0.005	0.002
	(0.519)	(0.016)	(0.014)	(0.030)	(0.010)	(0.007)
Held back a grade	-0.413	0.006	0.020	-0.038	-0.028	-0.011
	(0.875)	(0.016)	(0.047)	(0.067)	(0.026)	(0.008)
Total courses	0.219**	-0.003**	-0.002**	0.002	0.011**	0.006**
	(0.039)	(0.000)	(0.000)	(0.001)	(0.002)	(0.001)
Constant	44.637**	0.932**	0.715**	0.480**	0.181**	-0.008
	(0.347)	(0.007)	(0.011)	(0.007)	(0.016)	(0.006)

NOTE: Numbers in parentheses are standard errors.
N = 7,160
* $p < 0.05$
** $p < 0.01$

Table C-3. Fixed-effects estimates of the effect of total science, technology, engineering, and mathematics (OE/STEM) courses and academic math courses on math achievement

	Number-right score	Proficiency probability scores				
		Level 1	Level 2	Level 3	Level 4	Level 5
OE/STEM courses	0.013	0.002*	-0.008	-0.014	0.011**	0.001
	(0.151)	(0.001)	(0.011)	(0.016)	(0.003)	(0.001)
Academic math courses	1.431**	-0.000	0.004*	0.020**	0.051**	0.027**
	(0.096)	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)
Spring 2003–04 school year	2.52**	0.027**	0.062**	0.087	0.051**	-0.005
	(0.165)	(0.004)	0.010	(0.008)	(0.006)	(0.003)
Math homework	0.566*	-0.003	0.004	0.001	0.018**	0.015**
	(0.222)	(0.004)	(0.013)	(0.007)	(0.004)	(0.002)
Missing	-0.851	0.002	-0.025	-0.027**	-0.019**	-0.003
	(0.229)	(0.002)	(0.017)	(0.010)	(0.005)	(0.003)
Extracurricular activities	0.134	0.000	-0.011	0.001	0.014	0.001
	(0.524)	(0.004)	(0.012)	(0.011)	(0.011)	(0.001)
Missing	1.144**	-0.038	0.005	0.061**	0.060**	0.019**
	(0.287)	(0.004)	(0.017)	(0.007)	(0.004)	(0.003)
Employment	-0.088	-0.004	0.001	0.004	-0.002	-0.001
	(0.394)	(0.006)	(0.014)	(0.019)	(0.002)	(0.002)
Missing	-0.026	-0.020	-0.014	0.014	0.019**	0.003
	(0.581)	(0.012)	(0.023)	(0.036)	(0.006)	(0.001)
Importance of education	-0.169	0.001	-0.005	0.003	-0.004	-0.004
	(0.155)	(0.005)	(0.003)	(0.014)	(0.012)	(0.005)
Missing	0.303	-0.001	-0.001	-0.001	0.017	0.008*
	(0.472)	(0.004)	(0.030)	(0.032)	(0.009)	(0.003)
Expects college degree	1.043**	0.005	0.005	0.022	0.039**	0.010**
	(0.087)	(0.003)	(0.006)	(0.020)	(0.005)	(0.002)
Missing	-0.369	0.001	-0.004	-0.006	-0.012**	-0.009
	(0.439)	(0.008)	(0.020)	(0.005)	(0.003)	(0.005)
Constant	41.925**	0.936**	0.716	0.446	0.075**	-0.062**
	(0.392)	(0.007)	(0.009)	(0.010)	(0.014)	(0.004)
Math efficacy scale	0.211	0.002	0.007	0.014*	0.003	-0.002
	(0.178)	(0.003)	(0.005)	(0.007)	(0.006)	(0.001)
Missing	0.141	-0.003	-0.009	-0.009	0.013	0.007
	(0.121)	(0.005)	(0.004)	(0.011)	(0.008)	(0.003)
Parental investment scale	0.085	0.005	0.005	0.002	-0.003	-0.001
	(0.100)	(0.003)	(0.003)	(0.007)	(0.005)	(0.001)

See notes at end of table.

Table C-3. Fixed-effects estimates of the effect of total science, technology, engineering, and mathematics (OE/STEM) courses and academic math courses on math achievement–continued

	Number-right score	Proficiency probability scores				
		Level 1	Level 2	Level 3	Level 4	Level 5
Missing	0.034	-0.006	-0.006	0.019	0.004	0.001
	(0.456)	(0.013)	(0.012)	(0.032)	(0.008)	(0.006)
Held back a grade	-0.372	0.018	0.032	-0.037	-0.041	-0.017
	(0.710)	(0.016)	(0.040)	(0.062)	(0.008)	(0.002)
Constant	41.925**	0.936**	0.716	0.446	0.075**	-0.062**
	(0.392)	(0.007)	(0.009)	(0.010)	(0.014)	(0.004)

NOTE: Numbers in parentheses are standard errors.
N = 7,160
* $p < 0.05$
** $p < 0.01$

Table C-4. Fixed-effects estimates of the effect of the percentage of quantitative courses that are science, technology, engineering, and mathematics (OE/STEM) on math achievement

	Number-right score	Proficiency probability scores				
		Level 1	Level 2	Level 3	Level 4	Level 5
Percent OE/STEM courses	-0.277	0.062**	-0.020	-0.109	-0.001	0.000
	(1.070)	(0.021)	(0.074)	(0.107)	(0.039)	(0.018)
Spring 2003–04 school year	4.91**	0.026**	0.067**	0.120**	0.137**	0.042**
	(0.104)	(0.006)	(0.011)	(0.008)	(0.004)	(0.003)
Math homework	1.164**	-0.003	0.005	0.009*	0.040**	0.027**
	(0.153)	(0.005)	(0.012)	(0.005)	(0.006)	(0.001)
Missing	-1.078**	0.003*	-0.026	-0.031**	-0.027**	-0.008
	(0.244)	(0.001)	(0.015)	(0.011)	(0.004)	(0.004)
Extracurricular activities	0.192	0.005	-0.010	0.002	0.016	0.002
	(0.241)	(0.005)	(0.011)	(0.008)	(0.010)	(0.001)
Missing	1.292**	-0.041**	0.006	0.063**	0.066**	0.023**
	(0.198)	(0.011)	(0.012)	(0.005)	(0.006)	(0.004)
Employment	-0.055	-0.004	0.001	0.005	0.016	-0.000
	(0.256)	(0.007)	(0.012)	(0.017)	(0.010)	(0.002)
Missing	0.009	-0.020	-0.014	0.016	0.021	0.004
	(0.361)	(0.013)	(0.020)	(0.032)	(0.007)	(0.002)
Importance of education	-0.196	0.001	-0.004	0.002	-0.006	-0.004
	(0.114)	(0.006)	(0.003)	(0.013)	(0.013)	(0.006)
Missing	0.365	-0.002	-0.001	-0.001	0.020**	0.010**
	(0.333)	(0.002)	(0.027)	(0.033)	(0.002)	(0.001)
Expects college degree	1.197**	0.005	0.006	0.023	0.045**	0.013**
	(0.039)	(0.004)	(0.007)	(0.018)	(0.006)	(0.002)
Missing	-0.413*	0.000	-0.005	-0.006	-0.013*	-0.009
	(0.200)	(0.011)	(0.019)	(0.003)	(0.005)	(0.005)
Constant	44.281**	0.935**	0.722**	0.483**	0.159**	-0.018**
	(0.248)	(0.005)	(0.006)	(0.009)	(0.013)	(0.005)
Math efficacy scale	0.212	0.002	0.007	0.014	0.003	-0.002
	(0.184)	(0.002)	(0.005)	(0.007)	(0.006)	(0.001)

See notes at end of table.

Table C-4. Fixed-effects estimates of the effect of the percentage of quantitative courses that are science, technology, engineering, and mathematics (OE/STEM) on math achievement—continued

	Number-right score	Proficiency probability scores				
		Level 1	Level 2	Level 3	Level 4	Level 5
Missing	0.121	-0.004	-0.010	-0.009	0.013	0.007
	(0.143)	(0.005)	(0.005)	(0.010)	(0.008)	(0.002)
Parental investment scale	0.087	0.005	0.005	0.002	-0.003	-0.001
	(0.103)	(0.002)	(0.003)	(0.008)	(0.005)	(0.002)
Missing	0.022	-0.006	-0.007	0.016	0.003	0.001
	(0.468)	(0.011)	(0.012)	(0.033)	(0.009)	(0.006)
Held back a grade	-0.530	0.010	0.028	-0.035	-0.036	-0.016
	(0.710)	(0.020)	(0.046)	(0.072)	(0.007)	(0.003)
Total quantitative courses	1.161**	-0.001	0.002	0.015**	0.044**	0.022**
	(0.051)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)
Constant	44.281**	0.935**	0.722**	0.483**	0.159**	-0.018**
	(0.248)	(0.005)	(0.006)	(0.009)	(0.013)	(0.005)

NOTE: Numbers in parentheses are standard errors.
N = 7,160
* $p < 0.05$
** $p < 0.01$

Table C-5. Odds ratios from discrete time hazard regression models predicting dropping out of high school

	Model 1 (no controls)	Model 2 (with student controls)	Model 3 (no controls)	Model 4 (with student controls)	Model 5 (no controls)	Model 6 (with student controls)
Coursetaking						
Cumulative academic courses	0.73**	0.81**	—	—	—	—
Cumulative occupational courses	0.98	0.97	—	—	—	—
Cumulative percent occupational courses	—	—	13.76**	2.19*	—	—
Cumulative ratio of occupational courses to academic courses	—	—	—	—	6.69**	1.82*
Cumulative ratio of occupational courses to academic courses[2]	—	—	—	—	0.70*	0.90
Semester						
Spring 2001–02 (reference)	1.00	1.00	1.00	1.00	1.00	1.00
Fall 2002–03	4.00**	2.97**	1.71**	1.81**	1.72**	1.81**
Spring 2002–03	7.55**	5.11**	2.06**	2.36**	2.08**	2.37**
Fall 2003–04	18.37**	10.22**	2.29**	2.86**	2.32**	2.88**
Spring 2003–04	27.92**	14.69**	2.26**	3.15**	2.30**	3.16**
Fall 2004–05	1,466.89**	550.35**	105.02**	85.38**	107.17**	85.89**
Control variables						
American Indian	—	1.20	—	1.21	—	1.22
Asian	—	0.87	—	0.84	—	0.84
Black	—	0.80	—	0.85	—	0.85
Hispanic	—	1.16	—	1.16	—	1.16
More than one race	—	1.08	—	1.12	—	1.11
White (reference)	—	1.00	—	1.00	—	1.00

See notes at end of table.

Table C-5. Odds ratios from discrete time hazard regression models predicting dropping out of high school—continued

	Model 1 (no controls)	Model 2 (with student controls)	Model 3 (no controls)	Model 4 (with student controls)	Model 5 (no controls)	Model 6 (with student controls)
Poor	—	1.13	—	1.15	—	1.15
Nonnative English	—	1.19	—	1.24	—	1.25
Missing	—	1.30	—	1.12	—	1.12
Male	—	0.90	—	0.99	—	0.99
Mother-father family (reference)	—	1.00	—	1.00	—	1.00
Stepparent family	—	1.46**	—	1.53**	—	1.53**
Single parent family	—	1.40**	—	1.42**	—	1.42**
Other family form	—	1.38	—	1.54**	—	1.53**
Does not expect college (reference)	—	1.00	—	1.00	—	1.00
Expects some college	—	0.74*	—	0.72*	—	0.72*
Expects a 4-year degree	—	0.64**	—	0.56**	—	0.56**
Missing	—	0.97	—	1.01	—	1.01
Ever held back	—	1.73**	—	1.87**	—	1.86**
Missing	—	1.40**	—	1.51**	—	1.51**
Reading-math test scores		1.00		0.99		0.99
Missing	—	0.97	—	1.28	—	1.31
Parent did not attend college (reference)	—	1.00	—	1.00	—	1.00
Parent had some college	—	0.84	—	0.83	—	0.83
Parent graduated from college	—	0.76	—	0.71	—	0.71
Parent has a graduate degree	—	0.74	—	0.76	—	0.76
Academic disengagement	—	1.23	—	1.42	—	1.42
Missing	—	1.15	—	1.21	—	1.19
Academic preparation	—	1.14	—	1.12	—	1.11
Missing	—	1.45	—	1.58	—	1.55
Did not work (reference)	—	1.00	—	1.00	—	1.00
Had worked for pay	—	0.66	—	0.74	—	0.74

See notes at end of table.

Table C-5. Odds ratios from discrete time hazard regression models predicting dropping out of high school—continued

	Model 1 (no controls)	Model 2 (with student controls)	Model 3 (no controls)	Model 4 (with student controls)	Model 5 (no controls)	Model 6 (with student controls)
Missing	—	0.77	—	0.76*	—	0.76
Time spent on homework	—	1.01	—	1.01	—	1.01
Missing	—	0.54*	—	0.60	—	0.60
School poverty Q1—low (reference)	—	1.00	—	1.00	—	1.00
School poverty Q2	—	1.30	—	1.30	—	1.30
School poverty Q3	—	0.94	—	0.99	—	0.99
School poverty Q4—high	—	1.16	—	1.17	—	1.18
Missing	—	0.84	—	0.86	—	0.86
Northeast (reference)	—	1.00	—	1.00	—	1.00
Midwest	—	0.84	—	0.91	—	0.91
South	—	1.31	—	1.29	—	1.29
West	—	0.84	—	1.05	—	1.06
Urban (reference)	—	1.00	—	1.00	—	1.00
Suburban	—	0.69**	—	0.76*	—	0.76*
Rural	—	0.88	—	0.90	—	0.90
Ninth-grade GPA	—	0.58**	—	0.41**	—	0.41**
Missing	—	0.49	—	1.04	—	1.04

N = 11,300

Person-semesters at risk = 53,192.

* $p < 0.05$

** $p < 0.01$

Table C-6. Odds ratios from discrete time hazard regression models predicting dropping out of high school, with effects of number of failed academic courses

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Coursetaking						
Cumulative failed academic courses	1.11**	1.17**	1.17**	1.12**	1.19**	1.19**
Cumulative failed academic courses X cumulative occupational courses1	—	—	—	1.00	0.84	0.88**
Cumulative academic courses	0.84**	—	—	0.84**	—	—
Cumulative occupational courses	0.99	—	—	0.99	—	—
Cumulative percent occupational courses	—	2.26*	—	—	4.60**	—
Cumulative ratio of occupational courses to academic courses	—	—	2.13*	—	—	3.52**
Cumulative ratio of occupational courses to academic courses2	—	—	0.76	—	—	0.80
Semester						
Spring 2001–02 (reference)	1.00	1.00	1.00	1.00	1.00	1.00
Fall 2002–03	2.53**	1.68**	1.67**	2.52**	1.67**	1.68**
Spring 2002–03	3.99**	2.05**	2.04**	3.98**	2.04**	2.04**
Fall 2003–04	6.87**	2.34**	2.34**	6.87**	2.33**	2.33**
Spring 2003–04	9.39**	2.56**	2.56**	9.39**	2.54**	2.54**
Fall 2004–05	310.62**	62.05**	61.84**	311.74**	62.03**	61.88**
Control variables						
American Indian	1.09	1.08	1.07	1.10	1.10	1.10
Asian	0.85	0.82	0.82	0.85	0.82	0.822
Black	0.87	0.82	0.82	0.78	0.83	0.83
Hispanic	1.06	1.03	1.03	1.06	1.03	1.03
More than one race	1.06	1.08	1.08	1.06	1.10	1.11
White (reference)	1.00	1.00	1.00	1.00	1.00	1.00

See notes at end of table.

Table C-6. Odds ratios from discrete time hazard regression models predicting dropping out of high school, with effects for number of failed academic courses—continued

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Poor	1.12	1.12	1.12	1.12	1.13	1.13
Nonnative English	1.19	1.22	1.23	1.19	1.24	1.24
Missing	1.09	0.92	0.93	1.09	0.94	0.96
Male	0.90	0.97	0.97	0.90	0.97	0.96
Mother-father family (reference)	1.00	1.00	1.00	1.00	1.00	1.00
Stepparent family	1.49**	1.54**	1.54**	1.49**	1.53**	1.53**
Single parent family	1.41**	1.44**	1.44**	1.41**	1.43**	1.43**
Other family form	1.52*	1.68**	1.69**	1.52*	1.70**	1.72**
Does not expect college (reference)	1.00	1.00	1.00	1.00	1.00	1.00
Expects some college	0.75	0.73*	0.73	0.75	0.73*	0.73*
Expects a 4-year degree	0.64**	0.57**	0.57**	0.64**	0.57**	0.57**
Missing	0.97	0.99	0.99	0.96	0.99	0.99
Ever held back	1.69**	1.81**	1.81**	1.69**	1.81**	1.81**
Missing	1.37**	1.44**	1.44**	1.37**	1.43**	1.42**
Reading-math test scores	0.99	0.99*	0.98*	0.99	0.99*	0.99*
Missing	1.08	1.39	1.41	1.08	1.38	1.37
Parent did not attend college (reference)	1.00	1.00	1.00	1.00	1.00	1.00
Parent had some college	0.89	0.89	0.89	0.89	0.89	0.89
Parent graduated from college	0.72*	0.69**	0.69**	0.72*	0.69**	0.69**
Parent has a graduate degree	0.67	0.68**	0.68*	0.67*	0.69*	0.68*
Academic disengagement	1.30**	1.41**	1.41**	1.30**	1.41**	1.42**
Missing	1.22	1.42	1.41	1.22	1.38	1.36
Academic preparation	1.02	1.01	1.01	1.02	1.01	1.01
Missing	1.56	1.47	1.47	1.56	1.48	1.48
Did not work (reference)	1.00	1.00	1.00	1.00	1.00	1.00
Had worked for pay	0.64	0.69	0.70	0.64	0.70	0.71

See notes at end of table.

Table C-6. Odds ratios from discrete time hazard regression models predicting dropping out of high school, with effects for number of failed academic courses—continued

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Missing	0.77	0.76*	0.76*	0.77	0.76*	0.76*
Time spent on homework	1.00	1.01	1.01	1.00	1.00	1.01
Missing	0.58*	0.64	0.64	0.58*	0.64	0.64
School poverty Q1—low (reference)	1.00	1.00	1.00	1.00	1.00	1.00
School poverty Q2	1.32	1.33	1.33	1.32	1.31	1.30
School poverty Q3	0.97	1.01	1.01	0.97	1.00	0.99
School poverty Q4—high	1.12	1.11	1.11	1.12	1.09	1.08
Missing	0.81	0.82	0.81	0.81	0.81	0.81
Northeast (reference)	1.00	1.00	1.00	1.00	1.00	1.00
Midwest	0.83	0.88	0.87	0.83	0.88	0.88
South	1.27	1.24	1.24	1.28	1.27	1.27
West	0.84	0.97	0.97	0.84	0.99	1.00
Urban (reference)	1.00	1.00	1.00	1.00	1.00	1.00
Suburban	0.72*	0.78	0.78*	0.72**	0.78*	0.78*
Rural	0.79	0.99	0.99	0.95	0.99	0.97
Ninth-grade GPA	0.71***	0.60**	0.60**	0.71**	0.60**	0.60**
Missing	0.62	1.18	1.18	0.62	1.20	1.20

N = 11,300

Person-semesters at risk = 53,192

* $p < 0.05$

** $p < 0.01$

[1] Cumulative failed academic courses are interacted with cumulative occupational courses in model 4, with cumulative percent occupational courses in model 5, and with cumulative ratio of occupational to academic courses in model 6.

NOTE: All models contain student controls.