Balancing Career and Technical Education With Academic Coursework: The Consequences for Mathematics Achievement in High School

Author(s): Robert Bozick and Benjamin Dalton

Source: *Educational Evaluation and Policy Analysis*, June 2013, Vol. 35, No. 2 (June 2013), pp. 123-138

Published by: American Educational Research Association

Stable URL: https://www.jstor.org/stable/43773424

Educational Evaluation and Policy Analysis
June 2013, Vol. 35, No. 2, pp. 123–138
DOI: 10.3102/0162373712453870

Balancing Career and Technical Education With Academic Coursework: The Consequences for Mathematics Achievement in High School

Robert Bozick
RAND Corporation

Benjamin Dalton
RTI International

Federal legislation has attempted to move career and technical education (CTE) from a segregated component of the high school curriculum to an integrated element that jointly improves both academic and career readiness. However, concerns remain about the ability of CTE to improve academic learning. Using a nationally representative sample of high school students, we examine the relationship between CTE coursework and mathematics achievement in high school. Accounting for observed and unobserved characteristics of students, we find that CTE courses neither limit overall gains in mathematics learning nor the acquisition of basic and intermediate mathematics skills. Additionally, engineering and technology courses, a subset of CTE courses that incorporate quantitative reasoning, logic, and problem solving, are unrelated with math achievement.

Keywords: *career and technical education, vocational education, engineering courses, technology courses, math achievement*

Introduction

The dual goals of raising academic standards and improving workplace competencies, part of American education reform since the 1980s (National Commission on Excellence in Education, 1983; Secretary's Commission on Achieving Necessary Skills, 1991), have recently coalesced into new education models and policy proposals emphasizing an integrated model of college and career readiness for all secondary school graduates (Smerdon & Borman, 2012). With respect to college readiness, policymakers have had substantial success in increasing graduation requirements, establishing accountability systems, and forming quasi-national curriculum standards. With respect to career preparation, however, less is known about the long-standing attempt to transform historically narrow vocational education programs into a broader approach that integrates academic preparation with occupation-specific applications.

The 2006 passage of the Carl D. Perkins Career and Technical Education Act, commonly referred to as "Perkins IV," reflected the most recent national commitment to prepare youth for the evolving challenges of the workplace through occupationally focused coursework. As suggested by its name, Perkins IV is part of an ongoing series of legislative initiatives—Perkins II in 1990, the School-to-Work Opportunity Act of 1994, and Perkins III in 1998—that provides both a framework and funding to states and school districts to implement and/or maintain successful career and technical education (CTE) programs. A centerpiece of both the 1998 and 2006 legislation is the directive that occupational courses incorporate skills and concepts taught in core academic courses (e.g., math, science, and English) so that CTE supports academic achievement.

Perkins IV addresses the fact that high schools have historically maintained a divide between vocational education and academic/college-prep curricula (Castellano, Stringfield, & Stone, 2003).[1] With different goals, students, and oftentimes different teachers and separate areas of the school building, academic and occupational programs have been slow to join forces. As Castellano et al. (2003) observe, "vocational and academic staff often do not know each other well, much less collaborate with one another" (p. 249). Recent qualitative research finds that even though high schools with large CTE programs are working on integrating their academic and CTE curriculum in the wake of the Perkins IV legislation, many of the key structural supports—for example, teachers, local employers, and colleges—are not fully prepared or involved (Downing, Bozick, & Dalton, in press). Thus, it is unclear what implications the effort to integrate academics into CTE has for student achievement in academic areas.

This push for an integrated curriculum has also been accelerated by the movement to adopt the Common Core State Standards (CCSS)—a set of academically focused benchmarks in math and English developed by the National Governors Association and the Council of Chief State School Officers, currently being implemented in 48 states. The CCSS is a state-led initiative that articulates a consistent set of standards, designed and vetted by a team of school reform experts, to guide the formulation of a quasi-national curriculum. One criticism of the initiative is that business and industry had limited input, and as such, the standards reflect a narrow definition of academic proficiency with little attention paid to specific skills and knowledge valued in the workplace (National Association of State Directors of Career Technical Education Consortium, 2010). The adoption of the CCSS, with its heavy academic emphasis, alongside the curricular integration focus of Perkins IV, poses a challenge for schools and districts to design occupation-specific courses that effectively support core competencies in math and in English. Whether occupational courses can enhance academic achievement, or at a minimum not detract from it, will—whether fairly or not—remain a major standard by which CTE programs are evaluated.

To help understand the role of CTE in supporting academic achievement, the present study examines the acquisition of math proficiency for students attending high school from 2000–2001 through 2003–2004, on the eve of the passage of Perkins IV. While CTE encompasses a range of activities (e.g., occupational courses, job shadowing, internships), this study focuses only on the courses taken by students, with special attention paid to the implications of a curriculum that includes both academic and occupational courses. As such, this study gauges the relationship between CTE and math achievement at the start of the 21st century and, consequently, can inform the implementation of curricular programs under Perkins IV and the state-led CCSS initiative.

The Contributions and Limitations of Previous Research

Most research on the efficacy of vocational coursework relies on the assumption that occupationally focused courses can help bolster student achievement in academic areas (Plank, 2001). Because academic learning is most directly influenced by the concepts and skills taught in traditional academic courses, the mechanisms through which occupational course-taking affects overall achievement are more indirect. First, CTE courses may yield positive effects on learning if they substitute for less challenging general studies courses, other electives with less academic content, or study hall/free periods. Second, CTE courses can negatively affect learning by taking the place of academic courses in students' schedules, depriving them of opportunities for direct academic instruction. Thus, the relative balance of academic courses and CTE courses within students' overall course schedules are key to understanding potential occupational course effects. Third, CTE courses may improve academic learning by complementing specific academic subject skills. For example, engineering and technology courses (a subset of CTE courses) can improve academic achievement by making theoretical math and science concepts more concrete and relatable, particularly to students who may not be academically inclined.

To date, the research base on the academic implications of occupational course-taking has yielded mixed results. One of the more heavily cited studies is Plank's (2001) analysis of the National Education Longitudinal Study of 1988 (NELS:88), in which he found that the achievement gains of students who concentrated only in academic courses were greater than students who concentrated only in vocational courses and students who concentrated in both (i.e., "dual concentrators"). Agodini (2001) also analyzed NELS:88 and found that while academic concentrators had the greatest learning gains, dual concentrators learn more in math than vocational concentrators—suggesting that an integrated curriculum may yield more benefits than a strict vocational curriculum. In contrast, using a continuous indicator that identifies the number of credits earned in occupational courses rather than categorical indicators of occupational program participation, Rasinksi and Pedlow (1998) found that the total number of CTE courses taken had no relationship with learning gains in math.

While informative, studies that use either a categorical measure of curricular pathways such as that employed by Plank (2001) and Agodini (2001) or a continuous measure indicating the number of Carnegie units earned as employed by Rasinski and Pedlow (1998) are limited in that they do not capture the *relative balance* of CTE courses with academic courses. 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 by the criteria put forth by the National Center for Education Statistics (NCES), although Student B has both a higher *total* and a higher *percentage* of academic credits than Student B. These substantive differences are conflated in a simple categorical measure. Similarly, measuring the total number of credits earned is not sensitive to the practical constraints of students' course schedules, which are essentially a zero-sum arrangement: An additional course in an occupational subject often means one fewer course in an academic subject. These tradeoffs are not captured when simply summing total credits earned.

Whether using continuous or categorical measures of course-taking, these prior studies are limited in their ability to estimate the causal effects of occupational course-taking on achievement in the face of selection bias. A large body of research shows that students are not randomly placed into courses (Gamoran & Berends, 1987; Lucas, 1999; Oakes, 1985): When compared with their peers who follow a more traditional academic curriculum, students who enroll in vocational courses on average have fewer socioeconomic resources, such as lower family incomes and less educated parents, and lower levels of academic preparation, such as lower grades and standardized test scores (Levesque, Lauen, Teitelbaum, Alt, & Liebrera, 2000; Planty, Bozick, & Ingels, 2006; Rasinksi & Pedlow, 1998; Stone & Aliaga, 2007). Additionally, those who enroll in occupational courses are more likely to be African American, have a disability, and live in rural areas (Levesque et al., 2000; Stone & Aliaga, 2007). Though most studies control for observed socioeconomic and academic characteristics that influence course-taking, their findings are subject to selection bias due to their inability to account for unmeasured characteristics that select students into CTE.

The ideal way to eliminate this form of selection bias is to employ an experimental design with randomized control and treatment groups. Such studies of CTE course-taking, however, are sparse. The only experimental study of which we are aware is Stone, Alfeld, Pearson, Lewis, and Jensen's (2008) comparison of students of CTE teachers who worked collaboratively with math teachers to develop academically integrated CTE instructional activities (the treatment group) with students of CTE teachers who did not participate in such collaborations (the control group). They found that the treatment group performed better on standardized math tests than their peers in the control group—suggesting that in some instances, curricular integration may benefit academic learning. However, this study has limited relevance to the broader population of students who receive relatively isolated occupational instruction alongside their academic courses.

Taken together, the research to date paints a fuzzy portrait. Whether CTE has a positive, negative, or null effect on academic learning appears contingent on the measurement of course-taking and/or the methodological approach to deal with selection bias. As a consequence, the efficacy of an integrated academic-occupational curriculum lacks consistent empirical support.

Analytic Direction

To build upon and extend past research in this area, we attempt to alleviate two methodological limitations of prior studies: measurement problems regarding the structure of course-taking and selection bias. With respect to the measurement of course-taking, we use multiple measures of students' course schedules, including the total number of CTE courses taken as well as a measure that captures the relative mix of CTE and academic courses taken. This enables us to examine the independent influence of occupational courses under the premise that they substitute for academic courses. We also examine whether engineering and technology courses—a subset of CTE courses that emphasize quantitative skills, logic, and problem solving—are related with math achievement beyond what is learned from traditional math courses, under the premise that CTE can serve as a complement to the academic curriculum. With respect to selection bias, we use a two-period OLS regression model with student and year fixed-effects. This approach eliminates the potential confounding effects of unobserved time-invariant characteristics—thus providing stronger causal evidence than past research with observational data. We also include a rich array of control variables for time-varying experiences and attitudes that might bias our results.

Data and Methods

Data

For the present study, we analyze data from the Education Longitudinal Study of 2002 (ELS:2002). Conducted by the National Center for Education Statistics (NCES), ELS:2002 monitors the academic and developmental experiences of a cohort of 10th graders as they proceed through high school and into adulthood. ELS:2002 used a two-stage sampling procedure. In the first stage, a sample of 752 high schools, both public and private, were selected with probabilities proportional to their size. In the second stage, approximately 26 students were randomly sampled from each school on the condition that they were in the 10th grade in the spring term of 2002. Within the sample, 9,919 students completed a survey about their school and home experiences and were administered cognitive assessments in mathematics in both 2002 (10th grade) and in 2004 (12th grade).[2] Additionally, transcripts were collected from all participating sample members.

Our analysis is based on all public school sample members who were in-school sophomores in 2001–2002, participated in both the 10th grade and 12th grade interviews, completed the mathematics assessment, and have transcript information for all 4 years of high school. Because the Perkins legislation only provides funding to public schools and because the CCSS is only applicable to public schools, we exclude private school students from the analysis. The final analytic sample includes 7,160 public school students who participated in both the 10th and 12th grade interviews and math assessments.

Analytical Methods

We assess the effect of CTE courses on math learning in two ways. First, we assess the effect of the total number of CTE courses taken by estimating a two-period OLS regression model that accounts for measured and unmeasured student characteristics:

$$y_{it} = \beta_1 CTE_{it} + \beta_2 ACADEMIC_{it} + \delta \mathbf{X}_{it} + \alpha_i + \gamma_t + \varepsilon_{it}, \quad (1)$$

where y is the math test score for student i at time period t, t = 10th grade survey or 12th grade survey; *CTE* represents the total cumulative number of CTE courses taken by student i as of time t; *ACADEMIC* represents the total cumulative number of academic courses taken by student i as of time t; $\mathbf{X}$ is a vector of time-varying control variables for student i at time t; α_i is a fixed constant that differs for each student i (e.g., "student fixed-effects"); γ_i is a fixed constant that differs for each time period t (e.g., "year fixed-effects"); and ε is random error for student i at time t. In including student fixed-effects, the model is constrained to analyze only within-student variation over time. Therefore, time-invariant characteristics of students such as sex, race/ethnicity, personality, innate ability, and genetic makeup as well as period-invariant characteristics such as the structure of state/local education agencies or school leadership are effectively held constant. As a result, any potential bias owing to the differential selection of students into curricular programs—such as less affluent, academically disadvantaged students placed into occupational courses—is effectively removed. In experimental design terms, the "treatment" is CTE courses taken in high school. Thus, our key parameter of interest is β_1, which represents the effect on math achievement for each additional CTE course taken.

Second, we assess the effect of the relative balance of academic and CTE courses taken on math learning by estimating a similar two-period OLS regression model:

$$y_{it} = \beta_1 BALANCE_{it} + \delta \mathbf{X}_{it} + \alpha_i + \gamma_t + \varepsilon_{it} \quad (2)$$

This model is nearly identical to specification of Equation 1, except that *CTE* and *ACADEMIC* are now replaced with a single measure *BALANCE*, which is constructed as the proportion of total courses taken that are CTE. In experimental design terms, the "treatment" is having a course schedule where a higher proportion of courses are CTE, relative to having a course schedule where a higher proportion of courses are academic. Here our key parameter of interest is β_1, which represents the effect on math achievement for a course schedule where the proportional share of courses that are CTE increases by 1%. To examine the possibility of a more direct effect of CTE courses on math learning, we re-estimate both Equations 1 and 2 and replace our aggregate measure of occupational courses with engineering and technology courses.

Measures

Academic and occupational course-taking. The Secondary School Taxonomy, the course classification system used by NCES, classifies high school courses into four distinct curricula: academic, CTE, enrichment/other,[3] and special education. Our analysis is focused solely on academic and CTE courses, which comprise the lion's share of courses taken by high school students. The academic curriculum contains six subject areas: mathematics, science, English, social studies, fine arts, and non-English language. The CTE curriculum contains 10 occupational subject areas: agriculture and natural resources; engineering and technology; 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. Our analysis uses two variants of these course-taking variables: The first set focuses on academic courses and occupational courses in the aggregate, and the second set focuses more narrowly on math courses (a subset of academic courses) and engineering and technology courses (a subset of occupational courses). We describe each below.

The first set of variables uses the number of Carnegie units earned in occupational courses (*CTE* in Equation 1), the number of Carnegie units earned in academic courses (*ACADEMIC* in Equation 1), and the percentage of total Carnegie units earned that are classified as occupational (*BALANCE* in Equation 2). *CTE* and *ACADEMIC* measure the total number of courses earned and provide estimates of the average effect of an additional course in each subject area, controlling for credits earned in the other area. However, because students' course-taking choices are constrained by the number of periods available for study in the school day, an additional CTE course often means one fewer course in an academic subject (and vice versa). These tradeoffs are not captured in using *CTE* and *ACADEMIC* simultaneously. The third measure, *BALANCE*, accommodates the zero-sum nature of class schedules by calculating the percentage of total courses that are occupational: [total CTE credits / (total CTE credits + total academic credits)] * 100.

The second set of variables measures two specific types of academic and CTE courses: traditional math courses (a subset of academic courses) and engineering and technology courses (a subset of occupational courses). Traditional math courses include those that are part of a standard academic curriculum such as algebra, geometry, and calculus. Engineering and technology

TABLE 1
Descriptive Statistics

	10th Grade		12th Grade	
	M	*SD*	*M*	*SD*
Independent variables				
Total academic credits	10.0	2.0	18.9	3.4
Total occupational credits	0.8	0.9	2.5	2.0
% occupational credits	6.6	6.8	10.0	7.7
Total math credits	2.0	0.6	3.6	0.8
Total tech credits	0.1	0.2	0.2	0.5
% tech credits	2.2	7.7	2.9	7.9
Dependent variables				
Number-right score	46.2	12.1	50.6	12.5
Level 1—basic	0.93	0.15	0.96	0.10
Level 2—intermediate	0.72	0.35	0.79	0.32
Level 3—intermediate	0.52	0.40	0.63	0.40
Level 4—advanced	0.24	0.31	0.36	0.36
Level 5—advanced	0.01	0.06	0.04	0.13

Note. n = 7,160.

courses—herein referred to as "tech courses" for ease of expression—include CTE courses that incorporate quantitative skills, logic, and problem solving. Examples include mechanical drawing, electronic technology, automotive design, industrial production technology, and computer-assisted design/drafting. As with the first set of variables, we use three variables based on these courses: the number of Carnegie units earned in academic math courses (which we will use in place of *ACADEMIC*), the number of Carnegie units earned in tech courses (which we will use in place of *CTE*), and the percentage of Carnegie units earned in quantitative courses (math + tech courses) that are classified as tech (which we will use in place of *BALANCE*). The last measure is constructed as follows: [total tech credits / (total tech credits + total mathematics credits)] * 100.

The cumulative means of these course-taking measures, presented in Table 1, show that CTE course-taking occurs throughout all 4 years of high school, with slightly more occupational credits earned in the 11th and 12th grade than in the 9th and 10th grade.[4] 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 mathematics, tech courses were far less prevalent. The average student had earned 0.2 tech credits by the end of his or her senior year.

It is worth nothing that although divergent curricular tracks are indeed discernible in the ELS:2002 sample—that is, college-prep students enrolled in all academic courses with no complementary CTE courses, and vocational students taking mostly nonacademic courses—the majority of students in fact take a mix of both. In tabulations not shown in Table 1, we find that few students (14.0%) take academic courses exclusively. Exposure to CTE is relatively common: 64.1% of students earned at least two CTE credits and 43.4% earned three or more CTE credits. The former had accumulated an average of 18.3 academic credits, and the latter accumulated an average of 17.9 academic credits.

Mathematics achievement. The dependent variable y is mathematics achievement. Cognitive assessments in math, designed and scored using Item Response Theory (IRT), were administered to students in their schools during the 10th and 12th grade survey administrations. For this analysis, six measures of mathematics achievement based on these assessments are used: an overall estimated number-right score and five proficiency probability scores.

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 1).

A proficiency probability score is a criterion-referenced score indicating mastery of specific skills and knowledge across five hierarchical levels. Mastery of a higher level typically implies proficiency at lower levels. In contrast to the estimated number-right scores, which indicate overall test performance, the proficiency probability scores indicate what knowledge and skills the student does or does not possess. The five ordinal levels of math proficiency include:

- Level 1: simple arithmetic with whole numbers, such as multiplication or division of integers;
- Level 2: simple operations with decimals, fractions, powers, and roots;
- Level 3: intermediate problem solving, such as simplifying an algebraic expression;
- Level 4: advanced problem solving 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, such as the evaluation of functions.

The proficiency probability score at each level is a continuous measure ranging from 0 to 1, with 0 indicating nonmastery and 1 indicating mastery. The scores can be interpreted as the proportion of the population that has mastered the skills and knowledge defined for a given 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 1), indicating that by the end of 10th grade, 52% of the sample is proficient at Level 3. For the purposes of presentation and discussion, throughout our study Level 1 is considered basic skills, Levels 2 and 3 are considered intermediate skills, and Levels 4 and 5 are considered advanced skills.

As shown in Table 1, the greatest improvements in math achievement during the 11th and 12th grades occurred at Levels 3 and 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% to 63%), and the percentage of students proficient at Level 4 improved by about 12 percentage points (from 24% to 36%). By the end of senior year, nearly the entire sample was proficient at the most basic level (96% at Level 1), and very few were proficient at the most advanced level (4% at Level 5). Note, however, that these values are close to 100 and to 0 by design as a means to prevent ceiling and floor effects.

Control variables. Although the inclusion of student fixed-effects removes the potentially cofounding influences of time-invariant characteristics of students and their schools, time-varying influences could bias our results. For example, students' investments in school often change over time (Bozick, Alexander, Entwisle, Dauber, & Kerr, 2010). 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 rather than the true effect of coursework. Including a vector of time-varying controls (**X** in Equations 1 and 2) helps guard against this possibility.

We draw upon the rich information in ELS:2002 to construct control variables that have known relationships with student achievement, measured in both the 10th and 12th grade surveys. These variables include student's time use, student's orientation toward school, self-efficacy in math, parental involvement, and grade retention. The coding of these variables is included in the appendix. Because they are not central to the research questions we pose 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.

A final source of potential bias is any natural growth in mathematics skill that may occur between the test administrations. To eliminate the possibility of this "maturation effect," all models include year fixed-effects (γ_i) via a binary indicator of the survey year where "0" = 2001–2002 school year (10th grade interview and test administration) and "1" = 2003–2004 school year (12th grade interview and test administration) for each student.

Findings

Bivariate Relationships

Table 2 reports descriptive information on mean 12th grade test scores by students' cumulative course-taking histories through the spring of 2003–2004. Not surprisingly, students who had earned a large number of academic credits posted the highest test scores. 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. Conversely, students who take a larger number of occupational courses on average have lower scores on the mathematics assessment than their peers who take fewer occupational courses. For example, students who have earned three occupational course credits answered on average 50 questions correctly, while those who earned no occupational course credits answered 55 questions correctly. By and large, this overall finding holds when assessing different skill levels.

While in the aggregate, occupational courses show a negative relationship with test scores, this is not the case for all types of occupational courses. Tech courses, a subgroup of all CTE courses, incorporate quantitative skills, logic, and problem solving. The content of these courses should align more closely with the content on the test than occupational courses as a whole and is expected to complement the content taught in academic courses. The evidence here suggests that this might be the case: Students who earned two or more tech credits answered 55 questions correctly, while students who did not earn any tech credits answered 50 questions correctly. Moreover, almost half of students (49%) who earned two or more tech credits were proficient at Level 4, compared with 35% of their peers who did not earn any tech credits.

Effects of the Number and Percentage of Occupational Courses

Since observational data are used here with simple bivariate statistics, these associations cannot be used to evaluate the effect of CTE on achievement. To obtain an estimate of the causal effect of CTE course-taking, we estimate a series of two-period OLS regression models controlling for time-varying student characteristics, student fixed-effects, and year fixed-effects.[5] Table 3 shows the results for six models using the separate academic and occupational course measures (the Equation 1 specification described in our analytical approach). Each model contains an estimate for the number of academic courses and the number of occupational courses. The first column shows estimates from a model predicting the number-right score. The next five models estimate the effect of academic and occupational courses on the proficiency probability scores. Table 4 follows the same progression of models but replaces the separate credit measures with the single measure of the percent of courses that are occupational (the Equation 2 specification described in our analytical approach). Additionally, this model controls for the total number of credits earned.

The model predicting the number-right score in Table 3 shows that once potential confounds are accounted for, the total number of occupational courses taken is unrelated to the number

TABLE 2

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							
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							
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
Total tech credits							
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 math credits							
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

Note. $n = 7,160$.

TABLE 3

OLS 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 credits	–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	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 student time use, orientation toward school, self-efficacy in math, parental involvement, grade retention, student fixed-effects, and year-fixed-effects. $n = 7,160$.
$*p < 0.05$. $**p < 0.01$.

TABLE 4

OLS Estimates of the Effect of the Percentage of Total Courses That Are Occupational on Math Achievement

	Number-right score	Proficiency probability scores				
		Level 1	Level 2	Level 3	Level 4	Level 5
% occupational credits	–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 total number of credits earned, student time use, orientation toward school, self-efficacy in math, parental involvement, grade retention, student fixed-effects, and year-fixed-effects. $n = 7,160$.
$*p < 0.05$. $**p < 0.01$.

of questions answered correctly on the mathematics assessment. 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 4 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% 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.

While the model predicting number-right scores in Table 4 shows a negative relationship between occupational course-taking and achievement gains in math, it is not clear what skills and concepts are affected. To explore this, we examine the coefficients from the models predicting the proficiency probability scores. None of the occupational course-taking coefficients for Levels 1, 2, and 3 are significantly different from zero (Tables 3 and 4). 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 2 are spurious and that occupational courses do not limit gains in basic and intermediate math skills.

Levels 4 and 5 represent the most advanced skills and concepts on the ELS:2002 mathematics assessment. Not surprisingly, academic course-taking is positively related to learning gains at these levels. The coefficients for total academic courses taken are positive and significant (Table 3): 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 3): 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 course-taking has a positive effect on learning gains at both of the advanced levels and occupational course-taking 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 4 support this contention. The larger the percentage of occupational courses in one's course schedule, the lower the gains at Levels 4 and 5.

Predicted Math Gains for Different Course-taking Patterns

To get a sense of the magnitude of these effects, we estimated learning gains between the 10th and 12th grade test administrations based on the coefficients from the models in Table 4 and shown in Figures 1 and 2. Each predicted score assumes the student left 10th grade with an average score on the 10th grade math assessment and has average values on the time-varying control variables. Each figure displays the predicted scores for three sets of students following different course-taking patterns during the last 2 years of high school: students following an average mix of CTE and academic courses, occupational concentrators, and academic concentrators. The average course-taking pattern assumes that 15.2% 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). An occupational concentrator's course schedule was 28.6% occupational in the last 2 years of high school (7.5 academic courses and 3 occupational courses). An academic concentrator's course schedule was 0.0% occupational in the last 2 years of high school (10.5 academic courses and 0 occupational courses).

Figure 1 compares the predicted average number-right scores for students following different course-taking patterns during the last 2 years of high school.[6] Although the coefficient for "% occupational credits" 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,

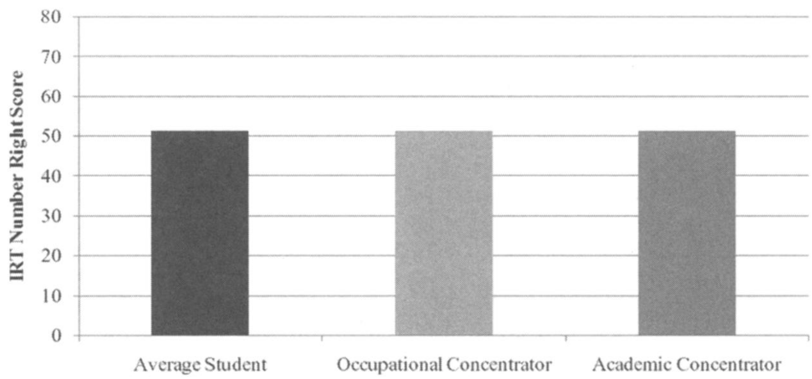

FIGURE 1. *Predicted 12th-Grade Number-Right Scores by Course-Taking Patterns*

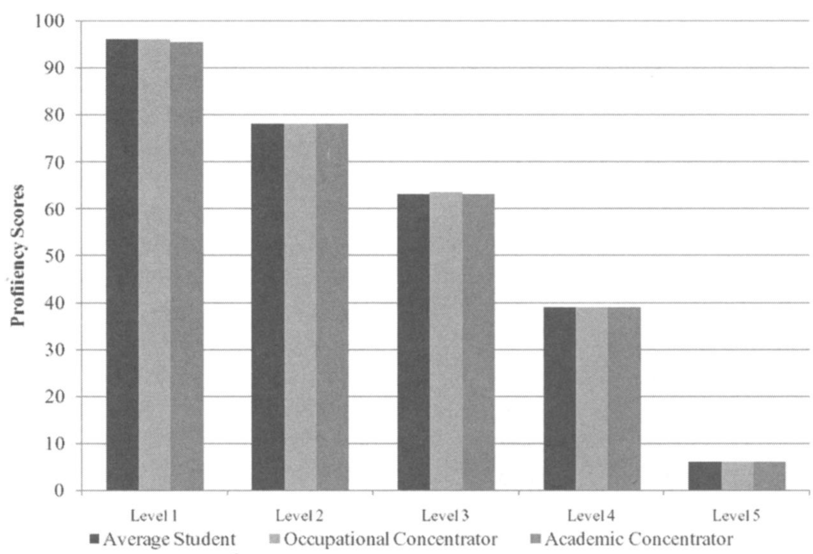

FIGURE 2. *Predicted 12th-Grade Number Proficiency Probability Scores by Course-Taking Patterns*

is quite small. All three course-taking patterns result in nearly identical predicted scores: All else being equal, students taking an average course schedule and academic concentrators would answer 51.3 questions correctly and occupational concentrators would answer 51.2 questions correctly. Substituting three CTE courses for three academic courses does not hinder math achievement.

To assess the specific types of skills and concepts learned, coefficients from the models predicting the proficiency probability scores are shown in Figure 2. Recall that the proficiency probability scores are interpreted as the proportion of the population that has mastered the skills and knowledge defined for that proficiency level. As an illustration, the first bar in the Level 1 cluster indicates that 96% of students would be proficient at Level 1 by the end of 12th grade if they followed the average course-taking pattern. With this interpretation in mind, the average student leaves high school with solid mastery of basic skills, moderate mastery of intermediate skills (78% at Level 2 and 63% at Level 3), and a low mastery of advanced skills (39% at Level 4 and 6% at Level 5).

TABLE 5

OLS Estimates of the Effect of Total Tech Courses and Math Courses on Math Achievement

		Proficiency probability scores				
	Number-right score	Level 1	Level 2	Level 3	Level 4	Level 5
Total tech credits	0.015	0.002	–0.009	–0.015	0.012**	0.001
	(0.097)	(0.001)	(0.006)	(0.015)	(0.004)	(0.001)
Total math credits	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 student time use, orientation toward school, self-efficacy in math, parental involvement, grade retention, student fixed-effects, and year-fixed-effects. $n = 7{,}160$.
$*p < 0.05$. $**p < 0.01$.

The main effects estimates in Table 4 indicate that course schedules with a greater percentage of occupational courses are associated with lower levels of proficiency in the advanced levels. However, as Figure 2 shows, the magnitude of these effects, much like those in the number-right score analysis, is very small. When comparing the scores of students following the different course-taking 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 a student taking zero occupational courses (0.39). This indicates that all things being equal, an occupational concentrator would have approximately the same mastery of Level 4 skills and concepts as the academic concentrator.

On the whole, the effects detected in our regression analyses are extremely minor: Students who take three occupational courses 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. A reminder is worth noting: As evidenced in Table 2, 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 directly attributable to the courses*, but likely to the characteristics of the students who take them.

Engineering and Technology Course-Taking

Our analysis concludes with an analysis of tech courses—a subset of occupational courses that are most likely to support the development of quantitative skills. We re-estimated Equations 1 and 2 to produce two sets of estimates. The first set is akin to those presented in Table 3, with the measure of total occupational credits earned replaced with total tech credits earned and the measure of total academic credits earned replaced with total math credits. The second set of estimates replaces the percentage of total credits that are occupational with the percentage of total credits in math and in tech courses that are classified as courses. Although the zero-sum relationship between math and tech courses is not the same as the academic-occupational tradeoff (i.e., one additional tech course does not necessarily mean one fewer math course), this measure broadly gauges the integration of quantitatively focused occupational courses into an overall mathematics curriculum.

Table 5 indicates that mathematics courses improve overall mathematics learning. Specifically, each additional academic mathematics course taken is associated with 1.4 more correct answers on mathematics assessment. Additionally, mathematics courses improve learning at all levels except Level 1. The relationship is strongest at the advanced levels. Tech courses, on the other hand, enhance mathematics learning only at Level 4. Each additional tech course is associated with a 0.012 increase in proficiency at Level 4—an effect, again, that is very small. Tech courses have no additional

TABLE 6

OLS Estimates of the Effect of the Percentage of Quantitative Courses That Are Tech Courses on Math Achievement

		Proficiency probability scores				
	Number-right score	Level 1	Level 2	Level 3	Level 4	Level 5
% tech credits	–0.028 (0.016)	0.001** (0.000)	–0.002 (0.001)	–0.002 (0.001)	–0.002** (0.001)	–0.001** (0.000)

Note. Quantitative courses include academic math courses and engineering and technology (tech) courses. Numbers in parentheses are standard errors. All models include controls for total number of math and tech credits earned, student time use, orientation toward school, self-efficacy in math, parental involvement, grade retention, student fixed-effects, and year-fixed-effects. $n = 7{,}160$.
*$p < 0.05$. **$p < 0.01$.

effect on the number-right score or proficiency at Levels 1, 2, 3, and 5.

Table 6 focuses on the percentage of quantitative courses (e.g., both math and tech courses) that are classified as tech. In this set of models, the coefficients are negative and significant at Levels 4 and 5: A percentage point increase in the percentage of courses that are classified as tech 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 tech course coefficient is positive at Level 4, the corresponding percent coefficient is negative. This suggests that any positive effect of tech course-taking is attenuated if not supplemented with traditional math courses. Regardless, these effects are also quite small in size. Taken together, the evidence here suggests that improving learning in mathematics is largely a function of traditional academic math courses. Tech courses neither boost nor compromise learning in math in any meaningful way.

Conclusion

One of the enduring themes across each iteration of the Perkins legislation is the integration of academic and occupational skills and concepts such that CTE students are prepared both for the world of higher education and work. In general, integration has typically been done in one of two ways: (1) an integrated course schedule, whereby CTE students take a mix of both academic and occupational courses, and (2) integrated course content, whereby the CTE courses taught at the school incorporate academic skills and applications and vice versa. Our findings provide some insight into whether these approaches can support math achievement. With respect to an integrated course schedule, we find that learning gains in math are not compromised when occupational courses are taken at the expense of academic courses. The development of advanced skills such as solving multistep word problems is slightly impeded when occupational courses comprise a larger share of students' course schedules. These statistically significant differences, however, are substantively inconsequential: The gains that accrue from taking all academic courses 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 ELS:2002 is an observational data set; none of the students were randomly assigned to different course-taking 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 high school, not the courses taken. It is not that coursework is inconsequential for learning, but that in a nationally representative sample, those who are high achievers gravitate to and/or are placed academic courses, while low achievers gravitate to and/or are placed 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 is small.

To examine integrated course content, we examined engineering and technology ("tech") courses—a subset of occupational courses that incorporates quantitative skills, problem solving, and logic. Similar to the findings for occupational courses overall, tech courses were largely unrelated to math achievement. Whether or not this is good news depends on the perspective. If the belief is that these courses should strengthen math achievement beyond what is typically learned in academic math courses, then this finding is disappointing. We find that math achievement is largely driven by traditional math courses, not the augmentation of or replacement with tech courses. If the belief is that tech courses are essential for the development of skills valued in the workplace, the verdict is still out. Without assessments that directly map onto particular occupational needs, the relevance of these findings to the broader goals of the Perkins legislation is unknown. At the very least, we know that among 10th graders in 2002, occupational courses did not impede math achievement—a finding that should assuage the concerns of those who worry that the expansion of CTE will undermine the efforts of CCSS to bolster proficiency in core academic areas.

Despite this "no harm" finding, proponents of the Perkins legislation should be concerned. The Perkins III act—enacted prior to the collection of ELS:2002—was a $20 million investment. This legislation emphasized the academic "upscaling" of CTE courses, with the hope that this would enhance their rigor and ultimately bolster academic achievement. These expectations, at least as of the time of the ELS:2002 study, have not materialized: Curricular integration, operationalized as a course schedule that includes occupational courses as supplements to regular academic courses, does not support math learning. Our findings raise the question of whether future investments in Perkins require an overhaul, as well as whether curricular restructuring initiatives aimed at improving core academic competencies, such as the CCSS, should include occupational courses. As the economy becomes increasingly reliant on industries characterized by advanced technology and communication, policymakers must grapple with the best ways to prepare youth for careers that require strong quantitative and analytical skills. Our findings cast doubt on the ability of occupational courses to effectively serve that role.

Appendix

Operationalization of Control Variables

Time-varying measures of student's time use (math homework, extracurricular activities, and employment), orientations toward school (importance of education and expects a college degree), self-efficacy in math, parental involvement, and grade retention are included in all fixed-effects regression models. Each is measured in both 10th grade and 12th grade. 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.

Notes

1. *Vocational education* was the term used before the 1998 passage of Perkins III. The phrase *CTE* replaced *vocational* to symbolically identify the new direction toward academic rigor and away from traditional occupational courses (e.g., shop class, home economics) that were often populated by non-college-bound students. For ease of expression, we use the terms *CTE*, *occupational*, and *vocational* equivalently throughout this article.

2. Of the 14,713 students who participated in both the 10th and 12th grade interviews, 13,328 participated in the 10th grade mathematics assessment, of which 9,919 participated in the 12th grade mathematics assessment. Only students who remained in the same school in both the 10th and 12th grades were administered the mathematics assessment. We excluded 334 cases because they had no transcript information and 129 cases because they lacked evidence of both a mathematics course and complete transcript information for both the 2002–2003 and 2003–2004 years. Of the remaining 9,456 cases, 2,296 attended a Catholic or other private school and were excluded from the analysis.

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

4. Regression models with individual-level fixed-effects, such as the ones we estimate, provide reliable estimates only when there is sufficient within-person variation in the key independent variable—in our analysis, occupational course-taking—across the observed periods of observation (Allison, 2005). ELS:2002 provides a large enough sample with sufficient within-person variation in occupational course-taking to support the estimation of a two-period model with student fixed-effects: Of the 7,160 students in our analytic sample, 78.7% had earned occupational credits between 10th and 12th grade with 63.9% earning one or more credit.

5. In our models, 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. Additionally, all standard errors were calculated using the cluster option in STATA to adjust for within-cluster (i.e., within-school) correlation.

6. Note that the bars do not represent the actual scores of students following different course-taking patterns, but rather what the average student is predicted to learn from the courses themselves—apart from any observed changes in our control variables, any time- and period-invariant factors that select them into different curricula (as captured by our inclusion of student fixed-effects), and any natural improvement in mathematics knowledge between the two survey administrations (as captured by our inclusion of year fixed-effects).

Acknowledgment

This research has benefitted from the comments of Michael Fong and Jay Noell of the U.S. Department of Education's Program and Policy Studies Service and members of the National Assessment of Career and Technical Education's Independent Advisory Panel. Any errors and all opinions are solely those of the authors.

References

Agodini, R. (2001). *Achievement effects of vocational and integrated studies*. Princeton, NJ: Mathematica Policy Research, Inc.

Allison, P. (2005). *Fixed effects regression methods for longitudinal data using SAS*. Cary, NC: SAS Institute.

Bozick, R., Alexander, K., Entwisle, D., Dauber, S., & Kerr, K. (2010). Framing the future: Revisiting the role of educational expectations in status attainment. *Social Forces*, *88*, 2027–2052.

Castellano, M., Stringfield, S., & Stone, J. R., III. (2003). Secondary career and technical education and comprehensive school reform: Implications for research and practice. *Review of Educational Research*, *73*, 231–272.

Downing, J., Bozick, R., & Dalton, B. (in press). *Implementing career and technical education following the passage of Perkins IV: A case study analysis*. Washington, DC: Policy and Program Studies Service, Office of Under Secretary, U.S. Department of Education.

Gamoran, A., & Berends, M. (1987). The effects of stratification in secondary schools: Synthesis of survey and ethnographic research. *Review of Educational Research, 57*, 415-435.

Levesque, K., Lauen, D., Teitelbaum, P., Alt, M., & Liebrera, S. (2000). *Vocational education in the United States: Toward the year 2000* (NCES 2000-029). Washington, DC: U.S. Department of Education.

Lucas, S. R. (1999). *Tracking inequality: Stratification and mobility in American high schools*. New York: Teachers' College Press.

National Association of State Directors of Career Technical Education Consortium. (2010). *CTE and common core standards*. Silver Spring, MD: Author.

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

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

Plank, S. (2001). A question of balance: CTE, academic courses, high school persistence, and student achievement. *Journal of Vocational Education Research, 26*, 279–327.

Planty, M., Bozick, R., & Ingels, S. (2006). *Academic pathways, preparation, and performance—A descriptive overview of the transcripts from the high school graduating class of 2003–04* (NCES 2007–316, U.S. Department of Education, National Center for Education Statistics). Washington, DC: U.S. Government Printing Office.

Rasinski, K. A., & Pedlow, S. (1998). The effect of high school vocational education on academic achievement gain and high school persistence: Evidence from NELS:88. In A. Gamoran (Ed.), *The quality of vocational education* (pp. 177–207). Washington, DC: National Institute on Postsecondary Education, Libraries, and Lifelong Learning.

Secretary's Commission on Achieving Necessary Skills (SCANS). (1991). *What work requires of schools*. Washington, DC: U.S. Department of Labor.

Smerdon, B., & Borman, K. M. (2012). *Pressing forward: Increasing and expanding rigor and relevance in America's high schools*. Charlotte, NC: Information Age Publishing.

Stone, J. R., III, Alfeld, C., Pearson, D., Lewis, M. V., & Jensen, S. (2008). Rigor and relevance: Enhancing high school students' math skills through career and technical education. *American Education Research Journal, 45*, 767–795.

Stone, J. R., III, & Aliaga, O. A. (2007). Participation in career and technical education, and school-to-work in American high schools. In D. Neumark (Ed.), *Improving school-to-work transitions* (pp. 59–86). New York: Russell Sage Foundation.

Authors

ROBERT BOZICK is a social scientist at the RAND Corporation, 1776 Main Street, P.O. Box 2138, Santa Monica, CA 90407-2138; email: rbozick@rand.org. His research focuses on the linkages between school and work over the life course, youth employment and youth labor markets, inequality in higher education, and the transition to adulthood for disadvantaged populations.

BENJAMIN DALTON is a research analyst in the Education Studies Division of RTI International. He specializes in high school studies, career and technical education, and international assessments.

Manuscript received April 13, 2011
Revision received May 8, 2011
Accepted May 24, 2012