Characteristics of Students Placed in College Remedial Mathematics:

Using the ELS 2002/2006 Data to Understand Remedial Mathematics Placements

by

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ABSTRACT

More than 30% of college entrants are placed in remedial mathematics (RM). Given that an explicit relationship exists between students' high school mathematics and college success in science, technology, engineering, and mathematical (STEM) fields, it is important to understand RM students' characteristics in high school.

Using the Education Longitudinal Survey 2002/2006 data, this study evaluated more than 130 variables for statistical and practical significance. The variables included standard demographic data, prior achievement and transcript data, family and teacher perceptions, school characteristics, and student attitudinal variables, all of which are identified as influential in mathematical success. These variables were analyzed using logistic regression models to estimate the likelihood that a student would be placed into RM.

As might be expected, student test scores, highest mathematics course taken, and high school grade point average were the strongest predictors of success in college mathematics courses. Attitude variables had a marginal effect on the most advantaged students, but their effect cannot be evaluated for disadvantaged students, due to a non-random pattern of missing data. Further research should concentrate on obtaining answers to the attitudinal questions and investigating their influence and interaction with academic indicators.

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TABLE OF CONTENTS

Page

Page

Page

LIST OF TABLES

Table Page

LIST OF FIGURES

Introduction

The twentieth century brought with it a change in attitude about education, opportunity, and advancement for United States (U.S.) citizens. Postsecondary education in the U.S. moved from a privilege of the wealthy to a goal of the majority and has become a nearly required element of social mobility. This phenomenon has driven a rise of those with a postsecondary education from 28% in 1973 to 59% in 2007 (NCES, 2009). This growth in college attendance has been accompanied by changes in the job market: Specifically, with increasing college attendance, graduates are moving away from manufacturing and agricultural jobs toward technology, education, and healthcare positions (Goyette, 2008; Tierney & Hagedorn, 2002). The wage premium earned by college graduates, while trending downward, remains (Barrow & Rouse, 2005; Carnevale, Smith, & Strohl, 2010; Long, 2010). In fact, Tierney and Hagedorn have suggested that “a college degree can no longer be considered a luxury, but rather a necessary passport to the middle class” (2002, p. 3).

The question remains whether U.S. high schools adequately prepare the majority of students for the requirements of a college education. The 2010 American College Test (ACT) College and Career Readiness Report found that only 24% of students met or surpassed ACTs target scores in English, Reading, Mathematics, and Science, whereas 28% of students met none of the benchmarks (ACT, 2010). Many students from groups who have historically not attended college are now seeking entry. The number of minorities, first-generation students, nontraditional students, and students living in poverty attending college has increased, as well as the number of underprepared students (Barbatis, 2008; Conway, 2009; Deil-Amen & DeLuca, 2010; Grimes & David, Fall; Jewett, 2008).

Underprepared students entering college is not new. Despite admission requirements of a good character, knowledge of Latin and Greek, and the ability to pay the tuition, in the 1700s students admitted to Harvard needed additional tutoring in both Latin and Greek (Stephens, 2003). In 1848, the University of Wisconsin established a department whose sole purpose was to tutor students on materials usually taught in secondary school (Stephens, 2003). Colleges and universities have long provided services to help students build academic skills and address skill deficits. *Remediation*, addressing the academic skills only, focuses on remedial courses in specific academic areas (e.g., mathematics) in which a student is weak. Remedial education has been subsumed under the broader heading of *developmental education*, which refers to services including tutoring, remedial courses, learning centers, study skills training, academic counseling, and more (NADE, 2010; Stephens, 2003). Developmental education provides underprepared students with a safe environment in which they can develop skills required for success in college-level courses (Payne & Lyman, 1996).

Recently, the extent to which developmental education services are available has escalated (Maxwell, 1997; Stephens, 2003). Approximately one third of all U.S. college students, and as many as 59% of students in two-year colleges, must enroll in developmental coursework (Bailey, Jeong, & Cho, 2010; Roueche & Waiwaiole, 2009). Providers of postsecondary education need to know as much about these students as possible. Early intervention, including while the student is still working through secondary school, may improve college completion rates and avoid the cost to both students and society of reteaching material previously covered.

Statement of the Problem

A longstanding disparity exists between the graduation requirements of high schools and the entry and success requirements of colleges and universities. U.S. Education Secretary Arne Duncan stated that K-12 and postsecondary education "have frequently operated as if they reside in different universes" (Lederman, 2010, para. 3), leaving a gap across which both sides point fingers but few bridges are built. High school standards are set by the states, which are only beginning to prepare common standards across states for high school graduation. Programs at the federal level, such as Race to the Top, are supplying funding to encourage schools to adopt the Common Core State Standards, aligning standards throughout the country, and encouraging higher standards for high school graduates to better prepare students for college and work (U.S. Department of Education, 2009). Yet these changes are just the latest round of raising high school graduation standards that have consistently resulted in the need for more remediation rather then less.

U.S. President Barack Obama continues to call for increasing college graduation rates as a tool for improving the economy and keeping the U.S. competitive (Shear, 2010), yet that goal depends on adequate preparation in high school. In response, 21 states have a high school diploma requirement that

Achieve, a bipartisan, non-profit education reform organization focused on making the transition from high school to college or the workforce seamless, considers *college- and career-ready* (i.e., including four years of English and Mathematics through at least Algebra 2; Achieve, 2010, p. 1). Nonetheless, there is little evidence that fewer students are requiring remediation once they reach college. Developmental placement is related to a 50% decrease in the likelihood of graduation from college (Bailey, 2009; Bettinger & Long, 2005; Florida Office of Program Policy Analysis and Government Accountability, 2007); thus, the President's agenda depends on reducing the need for developmental education.

Although developmental education itself is important, *remedial mathematics* (RM; a subset of developmental education focusing on mathematics skills) has garnered additional public attention (Ludwig, 2010). The current policy emphasis on Science, Technology, Engineering, and Mathematics (STEM) graduates leads to a focus on mathematics to enhance global competitiveness, future innovation, and economic success (NSF, 2007). The Race to the Top initiative grants additional points to states for emphasizing STEM educational efforts; this is the only listed priority that garners additional points, and it is second only to comprehensive reform on the Department of Education's priority list. An explicit positive relation exists between students' high school mathematics-course-taking patterns and college STEM graduation. The Department of Education's eventual goal is to "prepare more students for advanced study in the sciences, technology, engineering and mathematics" (U.S. Department of Education, 2009, p. 4).

At the same time more college students are placed into remedial mathematics than any other developmental service (Adelman, 2004a; 2004b; Parsad & Lewis, 2003; Strong American Schools, 2008). Remedial mathematics courses have passing rates as low as 30% (Attewell, Lavin, Domina, & Levey, 2006) with only 27% of students placed in remedial mathematics completing a bachelor's degree (Adelman, 1999). These disappointing results have led to remedial mathematics having a reputation as "the great logjam of higher education" (Ludwig, 2010, para. 2). Understanding who the affected students placed in RM courses are, identifying them early, and providing additional support before college is necessary.

Predominantly, researchers have examined high school mathematics course-taking or achievement in relation to more general college persistence, performance, and graduation (Adelman, 1999; Post et al., 2010; Trusty & Niles, 2003). Adelman (1999) specifically looked at students placed into remedial coursework, finding that the influence of high school academic measures (such as test scores and class rank) is larger than socioeconomic status (SES) or race/ethnicity. Bahr’s (2010a) work supported these findings, stating that "racial disparities in successful remediation in mathematics largely are a product of racial differences in mathematics skill at college entry" (p. 227). Taken together, there is a call for further investigation of student profiles in high school.

Investigating students and their academic resources while in high school may elucidate indicators of a developmental placement; this requires, however, a deeper understanding of the characteristics of the students in question, including academic elements (e.g., course-taking behaviors and achievement levels), as well as attitudinal elements (e.g., perceived self-efficacy and the level of effort they applied in high school).

Research Questions

This study addresses the following overarching question: *What characteristics and behaviors in high school can be used to predict which students will be placed into RM once they reach college?* Answering this question involved examining differences between those who reported being placed in RM and those who did not on several indicators:

- Academic indicators (e.g., courses taken, grades received, and mathematics test scores),
- Attitudes toward mathematics (e.g., self-efficacy, perception of the usefulness of mathematics, and the importance of getting good grades),
- Technological resources available to the student in their high school (e.g., access to computers in and out of class, use of calculators on mathematics assignments),
- Educational expectations from the student at several points, as well as from the parents and the student's tenth-grade mathematics teacher,
- Students' level of effort (e.g., how hard the student works, how many hours spent on homework, and teachers' reports of behavior in class),
- School level variables (e.g., *urbanicity*, percentage of students who receive free lunches, whether the student must pass a test to graduate)

and college-level variables (e.g., sector of control, location and level of entrance exams required – elements of which college-bound high school students are aware during college planning),

- Demographic information about the student (e.g., such as race/ethnicity, age, gender, SES, and parental education).

To answer this question I used the Education Longitudinal Study (ELS) 2002, produced by the National Center for Education Statistics (NCES). The survey contains three data collection events from a national sample of tenth graders: tenth grade, twelfth grade, and after either starting college or a career. The inclusion of academic items (e.g., achievement scores and mathematics courses taken) and attitudinal items (e.g., attitudes toward mathematics) make the ELS data uniquely suitable for investigating the questions above.

Organization of the Dissertation

In Chapter 2, I review and summarize the literature to highlight relevant background for the key variables. The goal was to produce a list with theoretical backing from a variety of sources and studies that provided focus to the study that follows. In Chapter 3, I discuss the data set and methodology used for the analysis, as well as limitations in interpretation and generalizability. Next, Chapter 4 includes a discussion of the analysis and results of the quantitative techniques used. Finally, in Chapter 5, I present conclusions and suggestions for future research.

Literature Review

This chapter represents a review of relevant theory and empirical research and is organized from general subject matter to specific variables of interest. First, I discuss developmental education in general, including its goals, history, and the public policy issues that are part of the national U.S. conversation. Next, I examine what is known about students placed in developmental education in general, about RM in particular and about the students placed in RM courses. I hypothesized that that there were significant, systematic differences between those students placed in RM and those who were not. Specific systematic differences expected between these groups included high-school-mathematics-course-taking, high school GPA and in the amount of homework time spent on mathematics courses. Therefore, this section includes what is known about homework time, high school GPA and course-taking, as these relate to college mathematics success. My second hypothesis was that there were significant, systematic differences in self-efficacy regarding mathematics achievement and other attitudes related to school between students placed into RM and comparable students not placed in RM. Thus, the fourth section includes an examination of literature regarding self-efficacy, attitudes, and the relation of these to mathematics achievement for students in RM.

Developmental Education in General

Purpose and goals of developmental education. The National Association for Developmental Education (NADE) is a professional organization that works to improve both the theory and practice of developmental education through professional development of practitioners, dissemination of exemplary models and facilitating communication among developmental education professionals. Their 2010 Fact Sheet lists the goals of developmental education:

- To provide educational opportunity for all individuals, appropriate to their needs, goals, and abilities
- To enhance the retention of students
- To ensure proper placement by assessing levels of academic preparedness
- To develop skills and attitudes necessary for the attainment of academic, career, and life goals
- To maintain academic standards while helping learners to acquire competencies needed for success in academic coursework
- To promote the development and application of cognitive and affective learning theory. (NADE, 2010)

The NADE’s goals focus on helping students of all levels and abilities to develop the necessary skills and attitudes for retention in school, completion of their program, and attainment of their long-term goals. RM is a subset of overall developmental education, although a crucial one in terms of degree completion. The definition put forth by the National Center for Developmental Education (NCDE, 2010) is similar:

> The field of developmental education supports the academic and personal growth of underprepared college students through instruction,

> counseling, advising, and tutoring. The clients of developmental education programs are traditional and nontraditional students who have been assessed as needing to develop their skills to be successful in college.

Although the NCDE's goals are not as comprehensive as NADE, the two premier organizations in developmental education are united in seeing developmental education as more than just the provision of remedial coursework. Both organizations define developmental education as extending to all types of skills related to college completion, including time management and study skills as well as subject-oriented academic achievement, but the organizations serve slightly different purposes. NCDE is a research institute within Appalachian State University, whereas NADE is a stand-alone professional development organization, with conferences and local chapters.

A common theme among proponents of providing developmental services at the college-level, evidenced in NADE's and NCDE's definitions, is that the goals of developmental education are aimed toward students' educational and occupational futures. In contrast, opponents of developmental education look backward, toward high school, claiming that students should have learned this material in high school (Parsad & Lewis, 2003). This tension has existed throughout the history of developmental education and remains a part of the public policy discussion today.

History of developmental education at the postsecondary level. The earliest colleges in the U.S. were founded by church groups with the goal of preparing the next generation of ministers (Stephens, 2003). Entrance requirements were that the student knew Latin and Greek, demonstrated good moral character, and could pay for their education either on their own or through their local community (Cremin, 1970). Students who were not proficient in Latin and Greek became the first set of underprepared students (Boylan, 1989; Payne & Lyman, 1996b).

Leaders of colleges and universities began to expand their search for students beyond future clergymen only to find that few individuals were sufficient prepared for college during their secondary coursework. Although many communities required primary education, secondary education was almost universally optional and available only to boys and those who could afford the tuition and the time off in which to study (Cremin, 1970; 1980). The numbers of students proficient in Latin and Greek decreased, forcing the existing colleges to accept students who did not meet their admissions standards and provide them academic assistance to address the deficiencies (Stephens, 2003).

The mid-1800s saw the rise of the public secondary school and the view of higher education as a means for social advancement (Boylan & White, 1987; Dotzler, 2003); the transition was not smooth, however, and the need for tutors to provide remedial education continued to be extensive (Boylan & White, 1987; Dotzler, 2003). During the same period, the entrance requirements for colleges steadily increased. For example, Yale did not require basic arithmetic as a prerequisite for admission until 1745, but by the beginning of the nineteenth century, Yale had increased the level of mathematics required for admission to

Euclidean geometry, previously part of the college curriculum (Rudy & Brubacher, 1997). As college entry requirements rose, so did the number of students without sufficient academic preparation. As early as 1855, Henry Tappan, the president of the University of Michigan, bemoaned the necessity of teaching courses that, in his view, should have been taught in secondary or even elementary schools (Stephens, 2003; Tappan, 1855). Puzzled by how to handle the influx of underprepared students, institutions created preparatory departments that were, essentially, secondary schools (Stephens, 2003), the precursors of today's developmental studies and learning support departments.

With the passing of the Morrill Act of 1862, which created land-grant colleges focused on agricultural or mechanical studies, the cost of higher education dropped yet again, and college became accessible to a wider range of students (Cremin, 1980; Stephens, 2003). This forced the expansion of preparatory departments to assist new students to improve their basic skills in reading, writing, and mathematics (Boylan, 1989; Payne & Lyman, 1996b; Tomlinson, 1989). The Morrill Act expanded the available courses of study at the colleges, increased aid to the land-grant colleges, and prohibited states that received funding from discriminating against any individual. "These colleges stood preeminently for the principle, increasingly important in the twentieth century, that every U.S. citizen is entitled to receive some form of higher education" (Rudy & Brubacher, 1997, p. 64).

In the late 1800s, more stringent admissions requirements were apparent. In 1870, the University of Michigan set their entrance requirements based on a minimum of a diploma from a secondary school. Harvard formulated an entrance examination; half of those who took it in 1879 failed and were admitted conditionally (Rudy & Brubacher, 1997; Stephens, 2003). Raising standards did little to reduce the amount of remediation required by incoming students.

Concurrently, women and newly freed slaves began entering institutions of higher education during the late 1800s. Both groups had previously been denied access to secondary education, so they required high levels of remediation to succeed (Boylan & White, 1987; Dotzler, 2003). Combined with the changes in standards, the amount of remedial education provided continued to rise.

In 1892, the National Education Association commissioned a report by the Committee of Ten, which included recommendations on better teacher training and a stronger secondary curriculum. The hope at the time was that by setting higher standards for secondary school students and teachers the number of underprepared students would drop (Stephens, 2003). By 1907, colleges had increased admissions requirements yet again, but the majority of students did not meet them. This led to the creation of developmental coursework intended to assist students to build up their academic skills (Payne & Lyman, 1996b; Stephens, 2003).

The Servicemen's Readjustment Act of 1944 (i.e., the *GI Bill of Rights* or *GI Bill*) provided financial assistance to most veterans of World War II. All but dishonorably discharged veterans were provided with access to a low- or no-cost college education (Dotzler, 2003). Many major state universities doubled or tripled their enrollments in as little as two years (Greenberg, 2008). By 1947, veterans made up 49% of all college students (Dotzler, 2003). Millions of these new college students required transitional programs, such as tutoring, special courses, counseling, and advising (Stephens, 2003).

Along with requiring a ramp-up in developmental services, the GI Bill changed how U.S. citizens viewed higher education, shifting a college education from a privilege of the elite to an opportunity for everyone (Greenberg, 2008). The attitude that college is available to everyone became part of the *American Dream* (Stephens, 2003).

At the same time, open admissions policies at the evolving community colleges led to large numbers of underprepared students and a concomitant increase in the demand for developmental education (Boylan, 1989; Payne & Lyman, 1996a; Tomlinson, 1989). With their focus on open admissions and access for all, community colleges have emerged as the most common, though not exclusive, provider of developmental education in the U.S.

Developmental education continues to be a significant part of the mission of community colleges; nearly all of them offer developmental coursework. The result has been a policy debate about providing developmental education only at community colleges and about the cost to the public of providing these services.

Public policy issues. Proponents of developmental education have argued that it is in everyone's best interest, in both social and economic terms, to provide educational opportunities to anyone with an interest in pursuing them (Crowe, 1998; Ignash, 1997; McCabe, 2000; Parsad & Lewis, 2003; Phelan, 2000; Roueche & Roueche, 2000). In contrast, opponents question whether developmental education is appropriate at all, because the material should have been covered within the curriculum of the public high school system, and whether it should ever be provided outside of the two-year college systems (Ignash, 1997; Levin, 2002; McCabe, 2000; Parsad & Lewis, 2003; Roueche & Roueche, 2000). The key issue that opponents raise is one of cost and funding (Hoyt & Sorensen, 2001; Saxon & Boylan, 2001).

Critics have argued that spending human academic resources on remedial education takes time and money away from other academic priorities (Kozeracki, 2002; Parsad & Lewis, 2003) while using public funds to pay a second time for students to learn skills that they should have been taught and mastered in high school (Hoyt & Sorensen, 2001; Parsad & Lewis, 2003). This has resulted in some educators' and legislators' considering transferring the funds spent on remedial education at the college-level to high schools to provide remediation prior to college-entrance (Ignash, 1997; Parsad & Lewis, 2003). In addition, these groups have called for increased collaboration between secondary and postsecondary institutions to improve students' skills before they reach college (Crowe, 1998; Parsad & Lewis, 2003). The call for higher standards, in the historical context of developmental education, highlights how each successive call for higher standards at the college-level has resulted in more – not less – remediation.

In 2001, the estimated cost of developmental education was less than 1% of funds annually allocated to postsecondary funding (Kozeracki, 2002). Advocates suggest that these costs are small and that the benefits far outweigh the cost for broader access to higher education. For example, the social benefits of a greater number of college graduates justify the financial cost of developmental education. Societies are likely to replenish the resources spent on developmental education through the increased tax revenue, greater productivity, increased consumption, workforce flexibility, lower crime rates, and overall better quality of civic life of college graduates (Kozeracki, 2002).

Several states and large urban public college systems have implemented or considered implementing restrictions on where developmental courses should be taught (Shaw, 1997). Ten states currently prevent public four-year institutions from offering remedial education, and more states continue to debate the issue (Jenkins & Boswell, 2002). Those who maintain that remedial coursework should remain outside four-year institutions and within the course offerings of community college argue that community colleges are better equipped to teach the courses and have the appropriate resources necessary to help students with both their skills and attitudes toward learning (Adelman, 2006; Kozeracki, 2002). Opponents worry that limiting developmental programs to community colleges will increase the stigma attached to the placement while reducing diversity of the four-year institutions (Kozeracki, 2002; Roueche & Roueche, 2000).

Researchers are just beginning to shed some light on the outcomes of limiting developmental coursework to community colleges. Parker and Richardson (2005) found that only 1,200 of the more than 4,500 students referred by the City University of New York (CUNY) four-year schools to the CUNY two-year schools for remediation actually enrolled. For those who enroll, taking developmental coursework in a community college separate from the student's four-year college reduces the likelihood of completing a Bachelor's degree by 15% (Duranczyk & Higbee, 2006). These limited findings suggest that segregating developmental education into community colleges decreases overall achievement and graduation in higher education, but replicated and expanded research is needed.

Developmental or remedial? What's in a name? Although *developmental* and *remedial* are used interchangeably to refer to these programs, the terms are not synonymous. This problem originates with usage of the term *remedial*. Through the 1960s the term most commonly used to describe these types of programs was *remedial education,* which implied a medical model: In the medical literature, a *remedy* must be found for a patient's illness, often in the form of a list of actions and/or prescription drugs. Similarly, a student's academic weakness(es) are identified and then *remedied*, using a prescriptive, focused program (Arendale, 2005).

The Civil Rights Movement brought a change in terminology, ushering in *compensatory education* language, as well as a change in the services to which the term referred. *Compensatory education* was designed to provide enrichment activities beyond academics: Advocates argued that the impoverished, discriminatory, and unsupportive environment in which many students grew up – with a timely emphasis on racial and ethnic minority students – contributed to the students' poor academic preparation (Arendale, 2005). Compensatory education was based on a public health model and addressed not only academic coursework but introduced students to a new type of learning that included cultural enrichment activities (Arendale, 2005).

In the 1970s the term *developmental education* emerged to refer to a comprehensive process that focuses on students' academic skills in addition to social and emotional development. One *part* of developmental education is *remedial education*, in the case of which precollege courses are provided to improve academic skills considered part of the high school curriculum but which students have yet to master by college entrance (Boylan & Bonham, 1999).

The term *remedial education* remains in use in federal legislation and regulation (Arendale, 2005; Boylan & Bonham, 1999). Although most advocates and educators prefer the term *developmental education*, critics argue that it is merely a euphemism for *remedial* and that it has assumed the negative connotations of there being something wrong with the patient/student that the earlier term implies. The use of the term *developmental education* to refer to programs for disabled or mentally retarded students in primary and secondary schools adds to the confusion and the stigmatization of students' taking *developmental* courses at the postsecondary level (Arendale, 2005).

In education and sociology research literatures, the term *remedial education* refers to a subset of *developmental education* focused on specific academic deficiencies, whereas *remedial education* is used as a blanket term in government reports and the economics literature to refer primarily to remedial subject-oriented coursework. Economics and government reports do not try to measure the other aspects of the broader developmental education services. In this study I use both terms. *Developmental education* is the blanket term, referring to coursework and other activities, including individual tutoring, study skills training, time management instruction and other services provided to underprepared students. *Remedial* specifically refers to subject-specific coursework.

The Developmental Education Student Population

Developmental education has been called the largest "hidden curriculum" on college campuses (Gubbe, 1999, p. 37). Student success in developmental coursework is related to participation in every other college program, including excelling in vocational, technical, or academic outlets. Completion of the developmental sequence is on the critical path to graduation for students referred to developmental services.

The rise in number of college students requiring developmental coursework has paralleled the rise in college-going rates (Provasnik & Planty, 2008). Seventy-six percent of all U.S. postsecondary institutions and 98% of community colleges offered developmental education and services for underprepared students, as of 2002 (Parsad & Lewis, 2003). Of the students surveyed for the National Education Longitudinal Study of 1988 (NELS:88) who attended only community colleges, 65% took at least one remedial course (Adelman, 2006).

Although Whites constitute the largest absolute number of students in developmental education, Black and Hispanic students are disproportionately represented. Adelman (2004a, p. 93) reported that 36% of Whites and 38% of

Asians were enrolled in developmental coursework, compared with 62% of Black and 63% of Hispanic students, a likely underestimation because of the exclusion of students from this study with fewer than 10 credits. This inequity points to a larger problem of college preparation for historically disadvantaged groups.

There are a few other key characteristics of students placed into developmental education coursework. Merisotis and Phipps (1998, 2000) noted that the majority of remedial students are returnees or delayed entrants to college, and they are often 20 years of age or older, whereas students not enrolled in remedial work are typically first-time college students immediately out of high school. Students from less-affluent families and for whom English is not native are overrepresented as well (Attewell et al., 2006). Students also display geographic diversity: Fifty-two percent of students from urban high schools were placed into remediation, compared to 40% of rural students and 38% of suburban students (Attewell et al., 2006). Thus race, ethnicity, SES, native language, delays in college entry, urbanicity of high school, and age are all characteristics that must be considered in any discussion of developmental students because students recommended for remedial coursework tend to disproportionately represent groups in these categories.

Placement tests can indicate that a student needs developmental services in one or more subjects, and these may require one or more remedial courses each (Bailey, Jeong, & Cho, 2010). Although most students (75%) tend to take three or fewer remedial courses (Attewell et al., 2006) they may require remediation in more than one subject area.

Students who enroll in and complete developmental coursework are more likely to have successful academic outcomes, yet the rates of completion are low. Although students who successfully complete remediation in one or more subjects have outcomes comparable to those who did not require any developmental coursework (Adelman, 2004a; Bahr, 2010b), only 25% of students successfully finish the remedial sequence to which they are referred (Bahr, 2008a).

Placement into Developmental Education

Several mechanisms are used to place students into developmental education. If a college or university requires an entrance examination, such as the Scholastic Aptitude Test (SAT) or the ACT, the score of that test is often used (ACT, 2010). If a student has taken either the SAT or the ACT he or she can submit that score to a school that does not require it in place of the school's standard placement test (Bailey et al., 2010). Some states, including Florida and Texas (until 2003), have statewide placement tests used at all state public colleges and universities with defined cutoff scores for placement into remedial courses (Martorell & McFarlin, 2010). For open enrollment schools and community colleges in the U.S., a placement test, such as COMPASS, ASSET, or ACCUPLACER, is administered to students before enrollment (Rao, 2004). The cut scores are set by each college and vary significantly. The lack of consistent cut scores can result in a student's being considered adequately prepared at one college and in need of remediation at another (Attewell et al., 2006; Rao, 2004). The type of school a student is attending, such as a two-year community college or a four-year university, matters to their likelihood of being placed in remedial courses as well: After controlling for social, demographic and academic backgrounds, Attewell et al. (2006) found that students of similar abilities were more likely to be placed into developmental coursework at two-year institutions than at four-year schools.

Developmental coursework is considered mandatory for students who score below the cut-off at 82% of colleges that offer developmental services, although it is inconsistently enforced. Institutions have stated limits regarding what other college-level courses students can take while completing any required developmental sequences, but only 1% enact this practice (Parsad & Lewis, 2003). Eighty-seven percent of colleges provide institutional credit toward financial aid, housing, or full-time status, but the credits do not transfer to other institutions and cannot be applied to a degree program. Additionally, only 4% of degree-granting institutions award elective credit toward a degree for completion of remedial coursework (Parsad & Lewis, 2003). Thus, despite necessary (and sometimes mandatory) placement into remedial courses, a student may spend time and money taking courses that will not count toward a culminating degree.

Students often fail to comply with the recommended course sequence prescribed by the placement tests. Only around 60% of students enroll in the developmental course or series of courses to which they were referred, whereas 30% never enroll in any developmental courses (Bailey et al., 2010). Hoyt (1999) found that students who attempted a course one level ahead of their placement earned, on average, a grade point average (GPA) of 1.7, or less than a "C" average. Many failed or withdrew from the course. These types of experiences exacerbate negative self-efficacy and demoralize both students and faculty members (Hoyt, 1999). Students who choose not to complete the recommended courses have a substantially higher dropout rate and a substantially lower graduation rate than other developmental students (Adelman, 1999; Boylan & Saxon, 1999).

Nearly a third of students referred did not enroll in a developmental course within three years of recommended placement. One third of these never completed any college-level courses within three years (Bailey, 2009). Usually, the failure to complete any college-level courses was the result of the student’s choice not to enroll in the developmental course in the first place, suggesting a considerable demoralizing effect on students when they receive the referral (Bailey et al., 2010).

For those who do enroll in referred developmental courses, there is the risk associated with being surrounded by equally underprepared students. Students just starting college build peer groups with students placed in the same courses. In this case, their peer groups consist of others placed in developmental courses, resulting in potential low-ability peer effects and poor overall subsequent student performance (Martorell & McFarlin, 2010).

Schools often try to mitigate the effect of the stigma that can be associated with developmental placements by hiding specific details about the student's placement. Students are told merely that their scores were "not on the high end" but that they also "weren't weak" (Deil-Amen & Rosenbaum, 2002, p. 257). Students are instructed that remedial coursework is a positive thing and that they are capable of doing the work with just a bit of help. This approach can improve student morale and interrupt the negative cycle of low expectations that can make student's academic performance worse.

Despite administrators’ positive intentions, this approach can backfire. Students enter college with a mental timeline and often a limited budget. They assume courses they are taking are applicable to their degree and transferable to other schools. Deil-Amen and Rosenbaum (2002) found that students who were unaware of the remedial status of their courses had not changed their timelines or budgets. In their study, 35% of students taking one remedial course believed that the course counted toward a degree and 28% were not sure. This misperception was greater among students taking three or more remedial courses: In this case, only 15% were aware that these courses did not count toward their degree (Deil-Amen & Rosenbaum, 2002).

The late discovery that courses do not count toward a degree has a variety of negative consequences. Students often fail to seek out or pass up alternative degrees or career paths that might be more in keeping with their skills and timelines. The remedial coursework must be paid for, either through financial aid or personal funds, an expense that may tip the cost-benefit equation for a student with many remedial requirements. The problem of credibility also exists: The college’s credibility is called into question for having concealed the precise nature of the coursework, as is the student’s credibility to their family for having established an unrealistic timeline to degree completion (Rosenbaum, 2004). Thus, placement in a developmental sequence brings risks. Unfortunately, there are additional subject-specific risks that come into play for students assigned to RM coursework.

Remedial Mathematics

RM is a subject-specific subset of developmental education intended to prepare students for College Algebra and other college-level mathematics courses. More schools offer RM than offer remedial writing or reading courses (Parsad & Lewis, 2003), perhaps because students require the most assistance in mathematics. Indeed, Attewell et al. (2006) found that mathematics was the most common remedial subject, with 28% of of students taking RM courses.

Little standardization among schools exists regarding the curriculum taught in RM. Schools vary in terms of whether they offer a single course intended to bring all students up to a college-level skill in mathematics or a series of courses beginning at arithmetic and continuing through Algebra I and II (Bailey et al., 2010; Clery, 2008; Penny & White, 1998; Waycaster, 2001). Of the 80 community colleges in the 15 *Achieving the Dream* states, the majority (66%) have reported three or more levels of courses in RM, with the rest split evenly between a single course and two courses (Bailey et al., 2010). Bailey et al. (2010) demonstrated that public two-year colleges offered an average of 3.6 remedial courses in mathematics in fall 2000, suggesting that more than three courses is relatively common. Cut scores on required placement tests are used to determine into which course a student is placed, with 33% of students referred to the lowest level course (basic arithmetic; Bailey et al., 2010). Regardless of the structure, the goal of RM is to ensure fluency in basic arithmetic, Algebra I, and Algebra 2.

Student population. Community colleges report that between 40% and 52% of their students are placed into RM, with RM classes having the lowest completion rate across subjects (Boylan & Saxon, 1999). Bahr (2008a, 2008b, 2010a) estimated that fewer than 25% of students who begin RM coursework complete it. Of those who complete a course, only 30% pass, suggesting that, for most students, remediation in mathematics requires more than one attempt (Attewell et al., 2006); however, the findings have not been consistent. Gerlaugh et. al. (2007) found that nearly 80% of community college students completed the required coursework, but only 68% of these received a "C" or better. Waycaster (2001) found similar levels of course completion, but a far worse percentage of students passing the course.

In contrast, students who attend and complete RM get better grades and are more likely to finish college than those who were placed into RM but do not take the courses. Boylan and Saxon (1999) found that completers retain critical subject information better than both students who were placed into but did not take RM and students who were not placed into RM at all. These findings suggest that once placed into RM, it is in the best long-term interests of the student to complete the course sequence.

High school grades and SAT scores seem logically related to a student's placement and success in RM, yet this is not always the case. Higbee and Thomas (1999) found no significant correlation between HS grades or SAT scores and the score a student achieved in a RM course. Nonetheless, ACT Inc., developed a cutoff score for the ACT college entrance exam based on a student's having a

50% probability of achieving a “B” and a 75% probability of achieving a “C” in the student's first college mathematics course. Of the 47% of 2010 high school graduates who took the ACT, only 43% met the cut-off score for mathematics (ACT, 2010).

Bahr (2008a) argued that the amount of required remediation is crucial when looking at student success after RM. Students who only require moderate remediation in mathematics and are placed into Intermediate Algebra (i.e., the equivalent of high school Algebra 2) have a 1 in 2 chance of successfully completing the remediation process, whereas those placed into basic arithmetic have a 1 in 15 chance of success (Bahr, 2008; 2010b).

Bahr (2007) also observed that the interaction of required remediation in both mathematics and English is multiplicative, not merely additive. To remediate successfully, a student must complete all referred developmental sequences in all subjects, not just mathematics. Students who show an explicit English deficiency are less likely to successfully remediate in mathematics (Bahr, 2010b).

Effect of race, ethnicity, or gender. Blacks, Hispanics, and Native Americans consistently score below Whites on all metrics beginning in kindergarten and continuing through twelfth grade (Bali & Alvarez, 2003; Braswell, Lutkus, et al., 2001; Fryer Jr & Levitt, 2004; 2006; Kao & Thompson, 2003; Riegle-Crumb, 2005; 2006). As they proceed through school, traditionally disadvantaged groups take less rigorous mathematics courses (Finn, Gerber, & Wang, 2002). The combined disadvantages of lower scores and less rigorous courses compound each other, such that by twelfth grade less than a quarter of

Blacks, Hispanics, and Native Americans are prepared for college-level mathematics (Rose & Betts, 2001). As a result, a disproportionate number of these students are placed into RM once they reach college (Adelman, 2004a; Bahr, 2010a; Walker & Plata, 2000). ACT (2010) found that only 13% of Blacks, 26% of American Indians/Alaska natives, and 27% of Hispanic students were college-ready in mathematics, compared with 52% of Whites and 68% of Asians, making it clear that the differences found in entry exams and course-passing rates exist prior to starting college.

Once placed in RM, there are also differences in completion and passing rates for historically disadvantaged groups. Walker and Plata (2000) found that fewer Blacks earned “As” than expected based on the overall grade distribution in RM courses, whereas more earned “Cs” or “Ds”. More Blacks also failed basic Algebra than expected. In addition, Black and Hispanic students tend to successfully complete their developmental sequences at lower rates than other groups (Bahr, 2010a; Hagedorn, Siadat, Fogel, Nora, & Pascarella, 1999). Specifically, the odds of a White student successfully remediating are 3.1 times the odds of success for a Black student and 1.6 times the odds of success for a Hispanic student (Bahr, 2010b). The majority of this difference is related to differences in mathematics skills at the time of entry into college. It is the deficiencies in mathematics with which the student enters that determine the placement of RM. This, in turn, has a significant relation to likelihood of successful remediation (Bahr, 2010b).

Conflicting evidence exists regarding gender and completion of RM. Stage and Kloosterman (1995) noted that success rates were lower for women. More recent studies have found no significant differences (Riegle-Crumb, 2005; Walker & Plata, 2000).

Remedial mathematics, college retention, and completion. Findings regarding retention and completion for RM students are inconsistent. Whereas some have found that RM is correlated with a higher likelihood of retention, other have found RM is related to lower retention.

Several recent studies have found a positive correlation between passing a mathematics RM course and retention (Fike & Fike, 2008; Lesik, 2007; Waycaster, 2001). Although the precise mechanism is unclear, improved self-efficacy is likely to encourage students to stay in college and continue their academic pursuits (Fike & Fike, 2008). For those students who complete the recommended coursework, RM has increased the likelihood of continuing college coursework and graduation (Boylan & Saxon, 1999; Gerlaugh et al., 2007).

In contrast, the U.S. Department of Education has found that only 45% of students who took two or more developmental courses completed any degree, compared with 56% of those who did not need any developmental coursework (NCES, 2004). The results are slightly worse for RM students specifically. Using an eight-year graduation window, only 42% of those placed into RM graduated (Wirt et al., 2004). Other researchers have confirmed the tendency of students placed in developmental coursework to drop out of college sooner than students who were not required to take developmental coursework (Burley, Butner, &

Cejda, 2001; Grimes, 1997; Hoyt, 1999). Bettinger and Long (2005) found that part-time students are more likely to drop out, complete fewer credits, and are less likely to complete a degree or transfer to a four-year school when placed in RM than full-time students placed into RM, although both have considerably worse outcomes than nonremedial students. Whichever direction the evidence finally points, a relation exists between placement into RM and a student's likelihood of staying in school and completing a degree. More research on this topic is needed before appropriate interventions can be developed.

Relation to high school mathematics coursework. High school mathematics coursework is generally organized into a hierarchical series of courses with progressively increasing levels of difficulty (Adelman, 1999; Riegle-Crumb, 2006). Each course builds on material covered in earlier courses, beginning with basic Algebra (Algebra I) in the eighth or ninth grade, to Geometry, Intermediate Algebra (Algebra II), Trigonometry, and Calculus. The coursework is cumulative, requiring that the student master each prior level before moving onward. Students who do not begin high school taking Algebra I or Geometry have little chance of reaching the more advanced courses, the strongest predictors of college attendance and completion (Adelman, 1999; Riegle-Crumb, 2006; Schneider, 2003).

Trusty and Niles (2003) found that students who take one class above Geometry (e.g., Algebra 2) have double the chance of graduating from college with a Bachelor's degree within six years, and each additional advanced mathematics course increases the likelihood of degree completion. Roth et al.

(2000) noted that Florida students who took Algebra 2 in high school, even if they received a "D", were less likely to be referred to RM. This finding supports the premise that familiarity with the material is more important for a student than detailed retention. Nonetheless, the further a student progresses in the high school mathematics course sequence, the better the college outcomes for that student.

As noted above, students show different achievement levels in high school mathematics based upon race or ethnicity. Riegle-Crumb (2006) found that, despite starting at the same level and after controlling for academic performance, Black and Hispanic students reach lower levels in the mathematics course sequence than White students.

Although even low grades in higher-level high school coursework are related to college graduation, taking higher-level classes in high school does not prevent students from being placed into RM courses in college. Hoyt and Sorensen (2001) looked at the students of a single college from two high school districts, reviewing transcript data as well as demographic characteristics. Results from logistic regression analyses predicting the likelihood of a student's placement into RM based upon ACT or COMPASS scores revealed that students who did not complete Intermediate Algebra were almost always placed in RM, but a few students who took higher levels of coursework, up to and including Calculus, were also placed into developmental coursework. Sorenson's study makes it clear that course-taking has a substantial effect on placement, but is not the entire story.

Other influences on mathematics achievement. Other elements of the high school experience are expected to influence mathematics achievement. Whether students complete their homework has been found to play a considerable role in academic preparation. Recent research findings indicate that students who do not complete homework received the equivalent of 1.2 years less of education. In contrast, completing 15 hours or more per week of homework was related to almost 1.5 additional years of education (Rosenbaum, 2004). This deficit could also influence placement into RM, although no study to date has explicitly looked at this question.

Mathematics achievement has been positively correlated with academic autonomy and perceived usefulness of math skills in life for RM students. Achievement in math is inversely related to mathematics anxiety, test anxiety, and self-efficacy with respect to a student's confidence in their ability to succeed in mathematics (Higbee & Thomas, 1999). Thus, where possible, these attitudinal variables must be included in attempts to better understand student achievement in remedial coursework specifically involving mathematics.

Remedial Mathematics and Attitudinal Variables

The ELS:2002/2006 survey, the data source for the present study, includes several types of attitude variables infrequently included in tests regarding RM. Previous work has primarily included *self-efficacy*, or the student’s belief in his or her ability to complete goals; however, the ELS survey also included three other types of attitudes that may play an important role in RM success: long-term educational expectations, extrinsic motivation, and persistence. Next, I review what is known about each of these attitudinal variables in relation to RM (or mathematics success in general when tests with RM are few).

Self-efficacy. Self-efficacy, defined as the perception an individual has of his or her ability to organize and execute the courses of action required to meet personal goals (Bandura, 1997), has been shown to influence academic achievement across all subject areas (Bandura, 1993; Zimmerman & Bandura, 1994), affecting grades, class work, homework, and examinations (Pintrich & De Groot, 1990). Students with a high level of self-efficacy try harder in school, pay more attention, and persevere longer facing difficult problems (Pajares & Kranzler, 1995). Even when controlling for other motivational variables (e.g., anxiety, self-concept, self-regulation, and engagement), self-efficacy predicted mathematics performance (Pajares & Graham, 1999). Self-efficacy may be even more critical to RM students because it is critical to perseverance and the level of effort students apply to learning difficult material (Bandura, 1997).

Bahr (2008a) noted that self-efficacy is strongly related to a student's ability to remediate successfully. Hall and Ponton (2005) argued that self-efficacy is based on past experiences and that either lack of exposure to mathematics or negative experiences in prior mathematics courses decreases the self-efficacy of developmental students. Given that SAT and high-school mathematics scores are not significant predictors of RM performance (Higbee & Thomas, 1999), this assertion requires further examination. The most direct assessment of self-efficacy in a RM environment showed that, compared with students enrolled in Calculus I, those enrolled in Intermediate Algebra (i.e., the highest level developmental course) scored significantly lower on the Mathematics Self-Efficacy Scale (Hall & Ponton, 2005).

Self-efficacy within the RM environment may be a double-edged sword. On the one hand, if self-efficacy is based on prior experiences, then the experience of succeeding in remedial coursework could improve the student's view of their own capabilities (Hall & Ponton, 2005). Stigma-free remediation, by concealing the nature of the coursework from the student, could result in increased self-efficacy for each course passed; however, should the student learn that work does not count toward graduation, the student could be demoralized, losing all improvements made in self-efficacy (Deil-Amen & Rosenbaum, 2002).

To protect their self-efficacy, students often choose to rationalize failure as outside of their control. In one study, the students blamed external factors (e.g., instructor characteristics) over items under their control (e.g., attendance) for their poor grades, presuming that the remedial course in which they were enrolled would not affect their ability to succeed in future courses (Wheland, Konet, & Butler, 2003). This was not the case. Fewer than 39% of those who received a “D” or worse in the remedial class achieved a “D” or better the next semester. This result speaks to treating classes as more than just remedial; students must learn not only the subject skills they are missing, but also to become aware of their own increased abilities to improve their senses of self-efficacy and position themselves for the rest of college (Hall & Ponton, 2005).

Expectations. Investigators have not thus far considered the student’s, parent’s, and teacher’s educational expectations within the specific context of

RM. There is evidence supporting the power of expectations in improving the level of learning that takes place in mathematics classrooms at the high school level (Bers, 2005; Flores, 2007), indicating that expectations can differentiate students. Muller (1998) explicitly tested whether parental educational expectations predict academic achievement: The influence of parents' expectations declines through high school until it has essentially no impact on high school seniors' achievement. Muller (1993) had previously written that parents socialize students' educational expectations, and there is a high degree of correlation between the parents' and students' educational expectations for students. With respect to the teacher's expectations, students in states with mandatory testing policies are less affected by teachers' expectations than students in states without such a testing policy (Muller & Schiller, 2000). This suggests that, while important, educational expectations can be overridden by other, more immediate, concerns, such as testing.

Students, parents, and teachers may also have expectations specifically regarding a student's performance or ability within a course. For example, students may expect themselves to meet a particular level of ability in mathematical problem-solving. McLeod and Adams (1989) put forth a cognitive-constructivist model of affect (e.g., emotion) in mathematics rooted in the discrepancy between the individuals' expectations and the demands of the mathematical activity in which they are taking part. Although this type of expectation is strongly tied to self-efficacy, in this context it refers to expectations about a specific problem or type. For example, a student may have a high level of self-efficacy in mathematics and still expect to get a particular problem wrong. These expectations influence student's affective response, which over time can change their level of self-efficacy.

Instrumental motivation. *Instrumental motivation*, or learning for a purpose, is generally considered the same psychological construct as *extrinsic motivation*. Both refer to a focus on grades, future earning-power, and other reasons to learn a subject that exist outside of the student. This is in contrast to *intrinsic motivation*, which is a student's desire for intellectual stimulation and intellectual curiosity about the subject they are studying.

Although the literature with respect to intrinsic/extrinsic motivation and learning is rich, the literature specific to motivation in the context of RM is less well-developed. In one investigation, students who were intrinsically motivated earned higher grades and were less anxious than students who were extrinsically motivated (Ironsmith, Marva, Harju, & Eppler, 2003). The approach of many RM programs, therefore, is not just to teach skills, but to increase intrinsic motivation in students (Newman-Ford, Lloyd, & Thomas, 2007).

In contrast to the desirable aspects of intrinsic motivation, extrinsic motivations are those that are based on outside forces. These are only as strong as the individual's desire for that external reward. Moreover, social psychologists have found that attempts to motivate students through extrinsic motivators, such as gold stars on a class performance chart, can backfire, resulting in the student's spending less time on the critical task than those who received no reward (Deci, Koestner, & Ryan, 1999; Deci, 1971; Lepper, Greene, & Nisbett, 1973). If this is the case, it would suggest that an excess of extrinsic motivators is the reason why some students are placed in RM, and not merely a symptom.

Action control. *Action control* refers to a student's ability to regulate behavior, put forth a sustained level of effort, and persist in the face of difficulties. Few studies have looked at how these traits might influence a student prior to placement in RM, but differences were found between students placed into RM and those who were not (Zimmerman & Schunk, 2001). Some research has been done on how to incorporate training in behavior regulation and persistence into remedial coursework in a way that is seamless with the subject-oriented materials (Trawick & Corno, 1995). This approach modestly improved short-term outcomes, although no further follow-up is available to determine whether long-term outcomes were affected. Persistence and self-regulation are also important in terms of engagement with RM materials: Students higher in persistence and self-regulation are more likely to succeed in the remedial course (Spence & Usher, 2007).

Other relevant attitudes. Research has also looked at elements such as student attitudes toward mathematics in terms of the gender-orientation of the subject (Stage & Kloosterman, 1995) and the usefulness of what is learned (McLeod & Adams, 1989). The question of whether mathematics is perceived as a male or female pursuit is beyond the scope of the present study, as no appropriate variables are available in the ELS:2002/2006 survey. Students were also not asked specifically about the perceived usefulness of mathematics, although some indirect inferences can be made from their responses to instrumental motivation items. The lack of appropriate items in the ELS survey precludes investigating these attitudes, which are mentioned in the mathematics motivation literature, but future research on these may further elucidate possible attitudinal influences in RM achievement.

Summary

The extant literature illustrates that some aspects of the research questions from Chapter 1 have partial answers. There appear to be systematic differences in mathematical course-taking in high school between those who are placed in RM and those who are not; the literature leaves unclear, however, whether these systematic differences are merely in taking particular courses or are tied to other resources, such as homework time and access to technology. There is also a difference in the level of self-efficacy in mathematics reported by those who are placed in RM in college versus those not in RM. It is unclear whether poor self-efficacy in high school could be related to placement in college RM, particularly when the student otherwise resembles more successful students.

This literature review informed the variables used in the analysis, the details of which will be discussed in the next chapter. The inclusion of attitudinal variables, in addition to demographic and test-score data, and the use of the most recent available national data set for the analysis differentiate this study from the previous literature. The next chapter discusses the technical details of how the analysis was carried out.

Methodology

In this chapter I review the data collected for this study and the techniques used to analyze those data. I also discuss the limitations of both the data and the analysis techniques.

Data: The Education Longitudinal Study of 2002

The NCES is located within the U.S. Department of Education, Institute of Education Sciences, and is tasked with collecting and analyzing data related to education in the U.S. (NCES, 2010a). The NCES has an extensive program on statistical standards that advises on the methodological and statistical aspects of data collection and analysis. The organization carries a congressional mandate for their data activities so that the data can be used to plan federal education programs, appropriate funds, and otherwise meet the educational needs of the U.S. citizenry. The NCES's several divisions are focused on designing studies, collecting data, or disseminating data and reports on particular groups of education consumers (e.g., groups focused on early childhood and international studies, postsecondary and adult education studies, and elementary/secondary studies).

The data from NCES's studies are made available not only to Congress, but to the public in the form of data analysis tools and downloadable data sets. States, the news media, business organizations, and other federal agencies (e.g., the Bureau of Labor Statistics and the National Science Foundation) use the data sets collected by NCES for a variety of analysis and forecasting purposes.

Researchers can download and analyze national data sets that would be difficult to collect on their own.

The current study uses a survey data set from the Division of Elementary and Secondary Studies, called the ELS of 2002. The ELS survey was explicitly designed to monitor the transition from high school to college and the workforce (NCES, 2010b). It is the next generation of a set of surveys to monitor this transition, including the NELS:88, High School and Beyond from 1980 (HS&B) and the National Longitudinal Study of the High School Class of 1972 (NLS-72).

The ELS survey assembled a national sample of students in tenth grade during the spring of 2002. In the first-year of data collection (2002) the high school sophomores completed a survey related to their attitudes and experiences. Students also completed baseline cognitive tests in reading and mathematics. Additional surveys were collected, gathering data from mathematics and English teachers, administrators, and parents to provide a comprehensive picture of the environment and influences of the student. The data set contains questionnaires from about 15,400 students and their parents, representing 750 U.S. schools (Bozick & Lauff, 2007). Oversampling was done with Catholic schools, private schools, and Asian students to ensure sufficient sample sizes (NCES, 2010c).

A follow-up survey was done in 2004 when most students from the original sample were seniors in high school. The goal of this follow-up was to measure achievement gains in mathematics, as well as to record changes in high school, early completion, dropout rates, and other changes in status. A second survey was administered to those from the base-year sample, as well as a mathematics cognitive test. In addition, the sample was *freshened*, whereby students who were seniors in 2004 but who had not been sophomores in the spring of 2002 (e.g., those out of the country or in a different grade) were given the chance for selection into the survey (NCES, 2010c). Thus, the 2004 follow-up sample is representative of 2004 spring's high school seniors in the U.S., although not all were in the original 2002 sample.

A second follow-up was completed in 2006 to collect information on the colleges to which the students applied, financial aid offers, enrollment in postsecondary institutions, as well as employment, earnings, living situation, and family formation. Respondents from both survey waves were included. Approximately 14,000 students from the original 2002 cohort responded to this second follow-up survey, a 10% decline from the original sample. In addition, high school transcript data were collected from which courses completed, grades, attendance, and course-taking patterns were added to the data set.

The result of these data collection efforts is a data set with two overarching characteristics. First, the data set is longitudinal, tracking the progression and performance of students who were sophomores in the spring of 2002 through to their early-adulthood outcomes (e.g., college, workforce) during the spring of 2006. This allows improvement to be measured and student characteristics at one point to be tied to outcomes later. Second, the data set is multilevel. Data about the student, their school, and their home environment were collected from several sources, such as parents, teachers, and administrators. This provides a comprehensive picture of the students, their environment, and their resources.

Of interest to researchers is the mixed achievement (e.g., test scores, transcript data) and attitudinal (e.g., questions about motivation and goals on the survey) approach of the survey. When combined with the varied perspectives of the multilevel approach, ELS provides a rich educational data source from which to explore student characteristics and changes across time.

The data are available in two forms: a public-use data set which can be downloaded by anyone, as well as a restricted-use data set. The principle difference is the presence of personally identifiable and quantitatively unique data in the restricted-use data set. For example, the restricted-use data set includes student's zip code, which can be linked to census tracking data (NCES, 2010d). This level of detail is not available in the public-use data set. In many cases, continuous variables available in the restricted-use data set are available in the public-use data set in categorized forms. For example, the restricted-use data set contains precise yearly earnings, whereas the public-use data set contains earnings grouped into categories.

A review of the more than 6,000 variables available resulted in only one potential variable of interest being unavailable for the present study. Specifically, student's residential "state" was of interest to assess whether there was a difference in reported placement into RM between students who live in states with a high-stakes exit examination and those who do not; this proved irrelevant, however, because the public-use data set contains a data element indicating whether a test is required to receive a high school diploma. The principle result of using the public data set is that several variables that are recorded as continuous in the restricted-use data set are categorical in the public data set and must be recoded into dummy variables. Because many of the questions of interest were discrete variables in the original surveys, the impact is minimal. Substantial documentation of the fields and data collection techniques is available. Information on response rates for the survey stages is included, with results ranging from 87% for the initial data collection (Ingels, Pratt, Rogers, Siegel, & Stutts, 2004) to 91% for the transcript collection (Ingels, Pratt, Rogers, Siegel, & Stutts, 2005; Ingels, Pratt, Wilson, Burns, Currivan, et al., 2007). The reader is referred to the Ingels et al. (2004; 2005; 2007) documentation for further information.

Data Elements Used

The key data element used to distinguish those who report taking a RM course and those who do not is F2B16C: "At [first attended postsecondary institution (F2PS1)], have you ever taken remedial or developmental courses to improve your Mathematics skills?” Sixty-four percent of students in the ELS data set have a valid answer to this question and will be the base sample for all further analyses. Of the remaining students, 24.5% are legitimately excluded because of factors such as not attending college, 1% responded to the second follow-up survey but left this item blank, and the remaining 10.5% did not respond to the second follow-up survey. Table 1 provides the breakdown of responses.

The basic unit of analysis of the ELS is the student; however, some variables have been created based on teacher, administrator, or parent surveys, and others reflect measurements of the student's school. These are distinguished in Tables 2 through 11. Each table contains a list of variables identified for analysis and the percentage of missing data from the students identified as having answered the core variable of interest. All variables were evaluated for differences between students reporting placement in RM and those who report not being placed in RM.

A very small number of variables collected during the second follow-up were included in this analysis. Variables from the second follow-up were only included if they could have been known to the student while in high school. Therefore, taking a college entrance exam, the entrance exam level of the college to which the student was applying, the college's sector and level of control, and whether the student would attend full or part time could be known in high school and were included.

Many of the variables of interest have more than 10% of their values missing. Where those variables are significantly different between students who report placement in RM and those who do not, further analysis was done to determine whether the remaining records are representative of the larger population.

In addition to the variables provided in the survey, two additional variables were calculated. The first was the race/ethnicity variable. XRACE was a recoded version of BYRACE that combined "Hispanic, race specified" and

"Hispanic, race not specified" into a single Hispanic category. The second variable indicated the highest level of mathematics a student completed in high school. The original highest mathematics course variable (F1HIMATH) combined Trigonometry, Pre-calculus, and Calculus into a single category. XHIMATH was created by combining the original highest mathematics course information with the specific list of courses taken to split Trigonometry, Pre-calculus, and Calculus into separate categories. These calculated variables had the same level of analysis and missing variables percentages as the original variables from which they were derived.

At the recommendation of the ELS documentation, several composite variables were examined along with the individual survey items that were used to calculate the composites. The documentation advises using the composite variables where available (Ingels et al., 2007), however these are complex to interpret. The composite variable for Socioeconomic Status (BYSES2) is based on the base year survey information and made up of five equally weighted variables: Father's education, mother's education, family income, father's occupation and mother's occupation. The occupational prestige value was based on the 1989 General Social Survey index. All values were taken first from the parent's survey, then from the student survey if the parent's survey was unavailable or the question wasn't answered, and finally imputed if possible. Each response is standardized to a z-score, and then the z-scores are averaged for the student. Students from single-parent households will have only that parent's education and occupation used for the calculation. Thus a socioeconomic status score of 1.00 indicates that the student averaged one standard deviation above the mean on all included variables. The variable was a continuous variable ranging from 2.11 to -1.98.

The attitudinal variables (mathematics self-efficacy, control expectation, instrumental motivation and action control) were each created using four or more individual questions. The answers were evaluated using factor analysis in order to create scoring factors, the results of which were standardized to a mean of 0 and a standard deviation of 1. All of the individual survey questions must have been answered in order to calculate a valid score for the composite variable. Details of the specific questions asked in order to create each composite variable are available in Appendix A.

To be included in the operating sample a student must have provided a valid answer to question F2B16C, so he or she must be a respondent for the second follow-up. The majority of students (92%) took part in all three survey rounds and had complete data. The remaining 8% of the students had various missing data elements because of nonparticipation or ineligibility for earlier survey rounds. Table 12 contains frequencies and percentages for these students.

Sample Weight

As with all NCES data products, the ELS data set contains a variety of weight variables for use in generalizing to the population. Sample weight F2BYWT is a panel weight for the second follow-up in 2006. Use of this weight requires that the sample is limited to those students who were in the 2002 sophomore cohort. To accommodate this requirement, 72 additional students who were part of the senior cohort and had no opportunity to participate in the sophomore cohort were removed from the analysis. The remaining students who did not complete the base-year survey were either nonrespondents (372) or ineligible (26). *Nonrespondents* were students who were part of the base-year (sophomore) cohort but chose not to respond. Ineligible students were part of the base-year cohort but were ineligible to complete the questionnaire because they were out of the country or had a disability that prevented their completing the survey. Because these students completed the later survey rounds, they remained in the sample.

Techniques

Three statistical techniques were used to analyze the ELS data. The preliminary analyses identified variables that were different between students who reported taking a RM course and those who did not. After the key variables were identified, they were used in a logistic regression to estimate the likelihood of a student's reporting placement in RM.

Preliminary analysis. The literature suggests a wide variety of potential variables, far more than can be included meaningfully in a logistic regression. As such, preliminary analyses, including Chi-square and *t*-tests, were used to reduce the number of variables entered into the models and to evaluate each variable for which there was evidence in the literature of an effect on placement.

All results in this section were evaluated against an *alpha* criterion of .05. In addition, following the lead of Bozick and Owings (2008), differences were required to meet an effect size criterion. Large data sets often result in small standard errors, which lead to small statistically significant differences. Given the size of the data set, an effect size criterion ensures that the findings are not only statistically significant, but practically significant as well.

Ferguson (2009) suggested that Chi-square effect sizes (Phi or Cramer's *V*) meet a threshold of .20, and that squared association measures, such as R^2, used with *t*-tests, meet a minimum of .04; however, this effect size threshold is stricter than the one proposed by Cohen (1992), who suggested Phi or Cramer's *V* of .10 and R^2 of .02. Throughout the analyses, effect sizes are noted.

Variables that prove statistically and practically significant were also evaluated for multicollinearity before use in the logistic regression. For example, family income is one of several elements of the composite variable *SES*. Where multicollinearity was found between variables, the one with higher explanatory power was retained.

Principle models. In the next stage of this study, I used logistic regression to estimate the likelihood that a student with a specific set of characteristics was placed in RM in college (Crisp et al., 2009). Logistic regression is a technique used with dichotomous variables (e.g., Yes/No): in this case, the dichotomous variable of students' reporting *Placed*/*Not Placed*. Dichotomous variables violate the assumptions of standard ordinary least squares regression, which require a linear relation between the predictor and predicted variables. Dichotomous variables exhibit a binomial distribution – an *S* curve, with a nearly flat proportion of possible values at first, a steep ascent approaching the second possible value, then a flattening out at the top. The nature of having two opposite, categorical variables as the predicted outcome makes it impossible for the distribution to be linear, because there are no values between the two variables of interest.

Logistic regression resolves the violated assumption by attempting to predict not the dichotomous variable, but the probability of belonging to the treatment case (those who report placement in RM). Logistic regression removes the requirement for a linear relation by using a logarithmic transformation, which results in a calculation of the odds (i.e., probability of being a treatment case divided by the probability of not being a treatment case) that the case is a treatment case.

Equation 1 is the formula for the logistic regression:

$$\hat{Y}_i = \frac{e^u}{1+e^u} \qquad [1]$$

where $\hat{Y}_i$ is the estimated probability that the *i*th case (i = 1, ... ,n) reports placement in RM. u is a linear regression equation of the form indicated in Equation 2:

$$u = A + B_1X_1 + B_2X_2 + ... + B_kX_k \qquad [2]$$

where A is the constant, B_k is the coefficient for the *k*th predictor and X_k is the predictor (Tabachnick & Fidell, 2006). The procedure estimates the coefficients using a maximum likelihood approach, meaning that the goal is to find the best combination of predictors that maximize the likelihood of obtaining the observed outcome frequencies.

The analysis was performed using SPSS version 18 and weighted by variable F2BYWT. Dummy variables were created for each categorical variable, with the reference group being the group with the highest frequency. By default, SPSS excludes the entire record if any one variable contains a missing value. Because of this and the high levels of missing values on the attitude variables in particular, two logistic regressions were performed: The first included only variables with less than 10% of records missing values, and the second included all variables identified as important based upon statistical and practical significance in the preliminary analyses.

Limitations

One limitation of the ELS data is the survey methodology itself, which relies on self-reported data. Fields can be left blank or filled in with false information, including the responses to critical variables in this analysis. For example, it is possible that some students who placed into a RM course chose to answer *No* to the question on the 2006 follow-up survey. If that were the case, this study would underestimate important data points. Adelman (1999) showed that student self-reporting about taking remedial courses, along with reports by college officials based on enrollments, underestimate the amount of remedial courses taken. College transcripts, as were used in Attewell’s (2006) study, are considered the most accurate way of identifying true rates of remedial course-taking. Because college transcripts are not yet available for the ELS study, some level of underestimation should be assumed in this study.

In addition, this study is not intended to be representative of students who started college more than two years after completing high school. At this time, the ELS study only follows the students through 2006, so students who took off more than two years and later started college, as well as all non-traditional students, are not included in the study.

Although logistic regression can estimate the odds of an individual's falling into a particular category, it does not establish a causal relation between one or more predictor variables and the outcome variable. Additionally, ELS is a single, albeit well-crafted, data set, and variables that fail to reach statistical significance with these data should not necessarily be assumed to be nonsignificant in other samples. Although efforts have been made to ensure that those chosen for analysis and those not chosen for analysis are not systematically different, sampling error is inherent in research and should be assumed present.

Results

I begin this chapter with a discussion of the previously identified variables from Tables 2 through 11. The section is divided into two sub-sections: (a) variables to be included in the logistic regression and (b) a brief discussion of the variables not included. I identify the variables with both statistically and practically significant results and discuss some descriptive statistics. A comprehensive table containing all of the variables, the test values, effect sizes, and percent missing is in Appendix B. In the second section, I present a series of logistic regression model results to assess the impact of each variable on the odds of a student's being placed in RM and improvements these variables contribute to the explanatory power of the model. Finally, the data are examined for sample bias. This includes comparing the students who answered the question regarding RM to those who did not, as well as an examination of the impact of missing values on the representativeness of the logistic regression models.

Descriptive Statistics

Of the 16,197 students in the ELS:2002/2006 sample, 3,979 never went to college and 1,864 did not respond to the question regarding placement in RM (F2B16C). In addition, a small number of students (72) were eliminated because they were not eligible for the initial survey, a requirement of the sample weight chosen for the study. This leaves an operating sample of 10,282 students who responded to the question regarding placement in RM. Once the sample weight is applied, the operating sample generalizes to 2,316,738 students.

Of the operating sample of 10,282 students, 3,099 (30.1%) reported being placed in RM (F2B16C). This is slightly higher than the 28% found by Attewell et al. (2006) using the NELS:88 data set, the nationally representative study that preceded the ELS:2002/2006 study. Since Attewell et al. (2006) used transcript data rather than self-report, there is a clear rise in the percentage of traditional college students being placed in RM.

Overall 39% of the operating sample reported taking at least one remedial class at their first postsecondary institution. Mathematics remains the largest remedial subject, with remedial writing reported by 26% of the operating sample and remedial reading reported by 19%. Table 13 shows the percentage of the operating sample in each possible combination of remedial coursework.

Variables Included in the Logistic Regression Models

Demographic and family situation variables. Of the 10 variables in the demographics and family situation category, two were considered further in this study. SES was included because it exceeded the effect size threshold, $t(1217004)=120.42$, $p < .001$, $r^2 = .12$, and race/ethnicity was included because of the large volume of literature suggesting its importance, $\chi^2(6, n = 2176469) = 17569.24$, $p < .001$, Cramer's $V = .09$.

Although the percentage of students from each racial or ethnic group (XRACE) was statistically comparable to the percentages for the entire ELS:2002/2006 study, Hispanic students were overrepresented in RM (35.9%). This difference was significant but did not meet the effect size threshold; given the large volume of literature suggesting that race/ethnicity is relevant, however, this variable was included in the logistic regression models despite its not reaching the effect size threshold.

The composite continuous variable for SES (BYSES2) was significantly different between students who reported taking RM in college and those who did not. The variable was a composite of tenth-grade family income, parental education, and parental job status. In each component variable, there was drop in the percentage of students reporting RM as the level of the variable rose. However none of the component variables met the effect size criteria. Only the composite met the effect size criteria and was included in the logistic regression models.

High school transcript and test variables. Of the 19 high school transcript and test variables listed in Table 3, only four were included in the logistic regression analyses: The two mathematics test scores (BYTXMSTD and F1TXMSTD), highest mathematics course taken (XHIMATH), and high school GPA (F1RGPP2) met the effect size thresholds. There were significant differences between students who reported taking RM and those who did not for both the base-year mathematics test score, $t(1386051)=305.09$, $p < .001$, $R^2 = .06$ and the follow-up mathematics test score, $t(1248676)=317.49$, $p < .001$, $R^2 = .08$. These tests were given explicitly to quantify the amount of skill a student gained between the base-year and the first follow-up (the student's senior year in high school) (Bozick & Owings, 2008); however, the gain score for students who report taking RM compared to those who do not did not meet the effect size target established.

The variable for highest mathematics course taken (XHIMATH) also met the effect size threshold, $\chi^2(6, n = 2216284) = 73708.57, p < .001$, Cramer's $V = .19$, as did those for the number of years of Pre-algebra (F1S17B), Algebra 1 (F1S17C), Algebra 2 (F1S17E), Trigonometry (F1S17F), Pre-calculus (F1S17G), and Calculus (F1S17H). Although there was a significant drop in the number of students who took Trigonometry, Pre-calculus, or Calculus reporting that they took RM in college, 19% of students who took Calculus, 23% of students who took Pre-calculus, and 28% of students who took Trigonometry reported taking RM. This is consistent with Hoyt's (1999) finding that even students who passed calculus in high school can end up in RM. The highest mathematics course completed variable was a composite created from the full set of subject-specific years completed variables (F1S17*). To avoid multicollinearity, only the XHIMATH variable (i.e., highest math course taken) was used in the logistic regression models.

Students with a high school GPA of 3.00 or below (F1RGPP2) made up 45% of the operating sample, yet they accounted for 55% of those who reported RM coursework. This difference is significant with an effect size that exceeds the threshold, $\chi^2(6, n = 2151794) = 55430.44, p < .001$, Cramer's $V = .16$.

Mathematics self-efficacy variables. The ELS:2002/2006 study contains a set of items intended to assess the level of mathematics self-efficacy that the student displayed at both the base-year and first follow-up surveys. Because this variable was identified as important in the literature, all of the related variables were assessed. The base-year self-efficacy variable (BYMATHSE) was a composite of several individual questions (see appendix A). Each individual variable and the composite variable were significant and met the effect size criteria, $t(796872)=115.22$, $p < .001$, $R^2 = .02$. Students who reported taking RM have 6% less mathematics self-efficacy than students who do not. During the first-year follow-up, a number of items were repeated and a new composite variable (F1MATHSE) was calculated, $t(738203)=141.92$, $p < .001$, $R^2 = .03$. In this case the students who reported taking RM have approximately 7% less mathematics self-efficacy than those who do not.

Based upon the suggestions in the ELS:2002/2006 documentation (Ingels et al., 2007), the composite variable was used in the logistic regression models rather than the individual variables. While this avoids multicollinearity between the individual question variables, a student must answer all of the items to have a composite score so there is a slightly higher rate of missing data (i.e., 31% for the base-year, 38% for the first follow-up) than there is for the individual items (i.e., which range from 24% to 29%).

Control expectation variables. The control expectation variables consisted of four specific questions (list in appendix A) and a continuous composite variable (BYCONEXP) based upon the four questions. All items were significant, and the composite variable met the effect size threshold, $t(701339)=83.12$, $p < .001$, $R^2 = .01$. As with self-efficacy, control expectation (BYCONEXP) had a higher rate of missing data (32%) than the individual items that contributed to it. Nonetheless, only the composite variable (BYCONEXP) was included in the models at the recommendation of the ELSs study designers.

Educational expectation variables. Educational expectations were collected in the base-year from the students (BYSTEXP) and the mathematics teacher (BYTM20). Expectations were collected again from the students in the first follow-up (F1STEXP). Student educational expectations at the first follow-up were significant predictors of RM, $\chi^2(5, n = 2227994) = 22154.65$, $p < .001$, Cramer's $V = .10$.

During the second follow-up, it was for the students either attending or planning to graduate from a four-year college that there were the largest percentage increases in assignment to RM (i.e., increases of 38% and 34% for those attending or planning to graduate, respectively); high aspirations had little to do with RM assignments, however, with 23% of those who expected to pursue a Ph.D., M.D. or other advanced degree and 28% of those who expected to pursue a Master's degree reporting that they took RM.

Teacher expectations (BYTM20), which contained more missing values than the student-provided expectations variable (24% compared to 4% missing), were significant and yielded one of the larger effect size measurements, $\chi^2(6, n = 1705558) = 44464.87$, $p < .001$, Cramer's $V = .16$. The teacher expectations variable was included in the logistic regression model.

Student action control variables. Student’s action control was also a composite variable (BYACTCTL) based on an assortment of items from the base-year survey. In addition, the base-year mathematics teacher was surveyed about many aspects of the student's effort and persistence, including time devoted to mathematics homework. Although many of the individual variables showed a statistically significant difference between students' reporting taking RM versus not, only a teacher item, BYTM16, which asked whether the student was attentive during class, met the effect size criteria, $\chi^2(4, n = 1792218) = 19273.03$, $p < .001$, Cramer's $V = .10$. Students whom the mathematics teacher reported as being attentive in class most or all of the time had a below-average rate of reporting RM (24%), compared to 35% RM for students who were attentive some of the time, rarely, or never.

High School or College-level Variables

The ELS:2002/2006 survey includes variables that were collected at the level of the school, and there is evidence in the literature to suggest they may be meaningful. Although all were statistically significant, none of the High School variables approached the effect size threshold. In contrast, several college-level variables which a student would be aware of in high school were significant and met the threshold.

The sector of control for the postsecondary school was significant and reached the effect size threshold, $\chi^2(8, n = 2307989) = 62870.44$, $p < .001$, Cramer's $V = .17$. Remediation was more common at public two-year institutions, where 40% of students reported taking a RM course. Public four-year institutions were the most common postsecondary institutions attended, but only 27% of students reported taking a RM course. Remediation was also more common at open admissions schools and schools whose entrance examination scores were in the lowest quartile, $\chi^2(3, n = 2046475) = 56351.57$, $p < .001$, Cramer's $V = .17$. Open admission schools were the most common type of school attended (37% of students); however, 17% of students attending a college whose entrance examination scores were in the highest quartile also reported taking RM. Based upon these results, college entrance examination quartiles (F2PS1EEX) was included in the logistic regression model.

Variables *Not* Included in the Logistic Regression Models

Instrumental motivation variables. As with the control expectation variables, the instrumental motivation variable group contained four survey questions as well as a composite variable (BYINSTMO) built from the response to the four individual variables. All five were significant, but none rose to the effect size threshold required for inclusion in the logistic regression model.

Technological resource variables. The base-year and first follow-up surveys both contained questions regarding the use of arithmetic calculators, graphing calculators, and computers in mathematics class. Several of these variables were significant but none rose to the effect size threshold required for inclusion in the logistic regression model.

College attendance variables. The literature suggested a relation between level of attendance (part- or full-time) and placement in RM. This variable was significant but did not meet the effect size criteria

Summary. As expected, due to the sample size, nearly all of the variables examined proved statistically significant. Only 13 met the threshold for practical significance. In addition, despite not meeting the threshold, race/ethnicity was controlled for in the model based upon existing literature suggesting its importance. The variables in Table 14 were used in the logistic regression analysis, listed in alphabetical order. All variables were significant at the $p < .001$ level for the difference between students who reported taking RM and those who did not.

Logistic Regression Models

The reference case for these models is a White student with a high school GPA between 3.01 and 3.50 who has completed Algebra 2 and plans to graduate with a Bachelor's degree from a four-year public college or university.

Model 1: Variables with < 10% missing values. Model 1 included all identified variables that were both statistically and practically significant in preliminary analyses and had less than 10% missing values. The result was the loss of 18% of the operating sample. Table 15 contains a partial list of the list of variables, regression coefficients, Wald test, and odds ratio for each of the statistically significant predictors using the criteria of $p < .05$. A complete table is available in Appendix C.

The model was significant, $\chi^2(36, n = 8422) = 132609.182$, $p < .001$, Nagelkerke $R^2 = .10$, indicating a small effect size. The model was able to correctly predict RM course-taking behavior in 71% of the cases. With respect to individual variables, all were significant except for the dummy variable indicating the student expected to complete less than a high school diploma and the dummy variable indicating no high school mathematics classes.

The impact of the base-year mathematics test score was substantial, with each additional point on the 67-point scale resulting in a 4% reduction in the likelihood of taking RM. High school GPA also matters: A student with a GPA over 3.51 is 20.2% less likely to take RM, whereas a student with a GPA between 2.01 and 2.50 is 23% more likely. With respect to mathematics coursework in high school, taking even one course after Algebra 2 resulted in a 31% decrease in the likelihood of taking RM.

SES had less influence than test scores or GPA on likelihood of taking RM courses, with each additional point (on a -2 to +2 possible scale) decreasing the likelihood of RM by 2%. Since a one point difference indicates a full standard deviation difference on all of the variables used to create the composite variable, the resulting change in likelihood of RM is very small.

Students attending a public two-year school are 16% more likely to be placed report placement in RM than those who attend a public four-year school. This confirms Attewell et al.’s (2006) finding that comparably skilled students are more likely to be placed in RM at a community college than at a public four-year institution.

Model 2: All variables. With all of the variables of interest from Table 14 included, the second model excluded 73% of the operating sample. The model was significant, $\chi^2(50, n = 2757) = 45344.245$, $p < .001$, Nagelkerke $R^2 = .11$, indicating a slightly larger effect size than was found with Model 1. The model was able to correctly predict RM course-taking behavior in 75% of the cases that were included. Table 16 contains selected coefficients, Wald tests, and odds ratios for this model. The full table is in Appendix C.

Base-year mathematics self-efficacy was not a statistically significant predictor in this model, although first follow-up mathematics self-efficacy remained statistically significant. On a scale of approximately -2 to +2, each additional point of mathematics self-efficacy in the last year of high school reduces the likelihood of RM by 9%. Control expectation showed a similar pattern, with a one point difference reducing the likelihood of a remedial placement by over 10%.

The impact of SES increased, with an additional point decreasing the likelihood of RM by 9%. Likewise, the impact of high school GPA remained strong, with a low GPA (i.e., between 1.51 and 2.00) resulting in a 65% increase in the likelihood of a student taking RM. The effect of the base-year mathematics test score remained the same, yielding a 4% reduction in the likelihood of taking RM for each additional point.

Additional mathematics coursework remained important, although more differentiation between the courses appeared. Taking Trigonometry reduced a student's likelihood of RM by nearly half, even if that was the only additional mathematics course taken, whereas Pre-calculus and Calculus only reduced the likelihood by approximately a quarter; however, the impact of not enough mathematics remained, with students stopping prior to Algebra 2 nearly twice as likely to be placed in RM as students who completed through Algebra 2.

A student’s level of attention paid in mathematics class only mattered when it was lacking. Students whose teachers reported they never paid attention in mathematics class were more than three times as likely to be placed in RM, whereas other levels of attention appeared to make only a marginal level of difference in student outcomes.

Sample Bias

Two potential types of sample bias could exist in this study. The first would be between the students who were included in the operating sample and those who were not. A student could be excluded because he or she had chosen not to go to college, had not responded to the second follow-up survey at all, or had not responded to the RM item itself when responding to the second follow-up survey. Each of these three groups was compared with students who were included in the operating sample. The 1% of students who explicitly did not answer the RM question were between the remedial and non-remedial groups on all traits. The larger group to be excluded consisted of students who did not respond to the second follow-up survey at all. These students most closely resembled students who chose not to go to college at all. Based upon these findings, the operating sample appears to be an unbiased representation of the broader group of students who chose to attend college.

The second type of sample bias comes from the missing data for students from the operating sample who remained in the logistic regressions after the case-wise exclusions of records with any missing values. In most cases nothing could be done about the missing variables. For example, a high level of missing values was found on many of the composite variables (i.e., including each of the attitudinal variables), caused by missing values in one or more of the variables used to construct the composite. Future research should investigate techniques for imputing the key attitudinal variables or calculating a score based on partial responses, where available.

Chi-square tests were done to compare the operating sample with the set of records used in Models 1 and 2. In all cases, the count of students for each of the key categorical data elements was significantly different between Model 1 and the operating sample and between Model 2 and the operating sample. Table 17 contains the detailed frequencies for the three groups on the most important variables.

Between Model 1 and the operating sample there were significant differences on all variables, with differences in race, high school GPA, and sector of operation for the college exceeding the previously defined effect sizes. The students in Model 1 were more likely to be White, have a modestly higher GPA, and be slightly more likely to attend a private, four-year school.

The differences were more pronounced between Model 2 and the operating sample. Again, all variables were statistically significant ($p < .001$), but there were additional practically significant differences in the highest mathematics class taken, student expectations, teacher expectations, base-year mathematics self-efficacy, and entrance exam requirements of the colleges attended. All of the effect sizes went up substantially, most moving from a small effect size to medium, with a few approaching large.

The most striking difference was in the racial make-up of the students in Model 2. Whereas Model 1 and the operating sample each contained approximately 11% Black students, Model 2 contained less than 1% – a 95% reduction. The percentage of Hispanic students in Model 2 was down 26% and the percentage of Native American students was down 54%. At the same time, White students increased from 59% of the operating sample to 71% of the students in Model 2. Racially, the complete records available for Model 2 were heavily biased and not representative of the broader population of students.

Model 2 also contained students whose GPAs were substantially higher, had taken more advanced mathematics courses, and were more likely to be enrolled in a four-year school. Even the schools chosen were different, with 20% more students attending schools whose entrance exam requirements were in the highest categories. With respect to the continuous variables, Table 18 contains the means for the operating sample, Model 1, and Model 2. Each of the continuous variables increased in Model 1, compared with the operating sample, and increased again in Model 2. Based upon these findings, it is necessary to conclude that the generalizability of Model 2 is substantially biased and the generalizability of Model 1 is somewhat biased due to the demographics of the missing cases when compared with the operating sample.

Discussion and Conclusion

I began this study with two hypotheses: that there would be systematic differences between students who reported placement in RM and those who did not on academic indicators (specifically GPA, course-taking behavior and time spent on homework), and on attitudinal variables (specifically self-efficacy, expectations, instrumental motivation and action control). The academic indicators were adequately tested using the ELS data, but the influence of the attitudinal variables remains unclear due to the substantial, non-random missing data. While this outcome is disappointing, there are some findings related to the academic indicators that can be discussed as well as implications of the missing data that must be considered.

Despite the self-reported nature of the ELS data, 30% of all students reported taking RM. It is likely that this under-represents the true percentage of students taking RM due to the similarity found between students who chose not to answer this specific question and students placed into RM, as well as the large pool of non-responders. It is also possible that students honestly did not realize that courses in which they were enrolled were remedial (Deil-Amen & Rosenbaum, 2002), so they answered "No" when in fact their answer should have been "Yes". Nonetheless this represents a 2% increase over Attewell et. al.'s (2006) transcript-based findings for a comparable group of traditional college students. A follow-up study after the 2012 data collection will be able to determine whether the self-reported data undercounted the prevalence of RM among traditional college students.

Answering the Question

The core question of this study asked was: *What characteristics and behaviors in high school can be used to predict which students will be placed into RM once they reach college?* Despite the wide array of statistically significant differences between those who reported placement into RM and those who did not, only a limited subset of characteristics in high school held predictive power that could be used as an early warning signal toward preventive efforts.

Demographic indicators. Hispanic students were the most over-represented group in RM, as were students for whom English is not their native language. Family incomes under $20,000 per year (i.e., between the four- and five-person poverty rate for 2002 [US Census Bureau, 2010]) were also over-represented. The mean SES for students who reported taking RM was nearly half the mean SES for students who did not report taking RM.

The impact found of socioeconomic status appears small, but the variable cannot be completely ignored. Ample evidence exists in the literature to suggest that SES is a meaningful predictor. There are two reasons why it may not, in this particular study, appear to provide a large impact. First, this variable is scaled too tightly to provide any real granularity for analysis. One additional point on the scale equates to a full standard deviation on average for all five component variables. One of the components could be having a significant issue but the averaging process masks that impact. Second, there is evidence in the literature that SES could be having an indirect effect on RM placement by affecting the academic indicators. If that is the case, there may be little influence left to be explained.

Academic indicators. The strongest predictors of RM placement available while the student was still in high school were the score on the base-year mathematics test and the highest mathematics course taken. Although the mathematics test included with the ELS survey was compiled specifically for this study, it was made up of items from other assessments, including NELS:88, the National Assessment of Educational Progress (NAEP) and the Program for International Student Assessment (PISA ;Ingels, Pratt, Rogers, Siegel, & Stutts, 2004). The scaling was defined to allow comparison between students and was primarily useful for sorting individuals into rank-order within their peer group. A well-designed alternative test (e.g., a state high school exit exam or college entrance exam) could be used for a similar analysis. Standardizing the alternative test to the mean of 50 and standard deviation of 10 used for the ELS test would allow comparable analysis to be done of the estimated impact of an additional point on the alternative test. Regardless of how it was used, it is clear that a standardized test at approximately tenth grade may provide a meaningful indication of where a student stands with respect to an eventual RM placement and an operationally achievable early warning system for students who are at risk of a remedial placement.

Although it is impossible to say what the highest mathematics course a student will have completed prior to the end of high school until the student graduates from high school, a policy initiative to increase the number of mathematics courses required for high school graduation shows promise in reducing the overall rate of remediation required. Taking additional mathematics classes is not a guarantee of avoiding RM as the 19% of students who took calculus yet reported taking RM can attest. Nonetheless, one additional mathematics course reduced the likelihood of RM by nearly one third. Without a formal experiment, it is impossible to know whether forcing additional mathematics courses on all students would have an equally positive impact. What we do know is that there was a significant difference in the number of years of mathematics required for graduation between students who reported taking RM and those who did not, although the effect size was below the threshold. A quasi-experiment could be performed as states raise their minimum graduation requirements to require one course past Algebra 2 in order to assess the impact within the context of the overall curriculum.

Attitudinal variables. Self-efficacy appeared to have little impact on the models and add little explanatory power when included. What power it did have was overshadowed by more concrete variables such as GPA, test scores, and courses taken. Control expectation had a similarly minor impact, and the other attitudinal variables failed to meet the necessary effect size criteria. It is possible that the small direct impact of these variables is due to a much larger indirect effect on the academic variables listed above. As with socioeconomic status, if the effect of the attitudinal variables is embedded in the test scores, GPA and course taking behavior, there would be little influence left to explain. The bias found in the sample of students for whom the attitude variables are available, however, suggests a more subtle conclusion. Attitudes may have a small effect on White, academically superior students, but these data provide little insight into the effect improved attitudes can have on the most vulnerable students. The near absence of Black students, 54% reduction in Native American students, and 26% reduction in Hispanic students in Model 2 make it impossible to say whether there is an independent effect of attitude for these group. We cannot draw conclusions about the impact of attitudes on these student populations without additional data-gathering efforts aimed specifically at disadvantaged groups.

Although the predictive power of the tenth-grade-mathematics teacher's educational expectations was minimal, the significance of the difference between students who reported placement in RM and those who did not was surprisingly high. This suggests that teachers are able to accurately read the combination of skill and motivation their students displayed in class to come up with a prediction, but have little ability through their expectations to influence the outcome. Only the student's educational expectations appear to meaningfully influence their likelihood of taking RM, and then only at the end of high school. Moreover, clarity of purpose appears more important than what the student's expectations are, as students who had a specific expectation of completing a college-level program, regardless of its level, were less likely to take RM.

With so many statistically significant variables, it seems surprising to find so few that are actionable. Most of the variables used in the models moved the needle only a few points. Those with a larger impact tend to be intuitively obvious:

1. *Monitoring of student GPAs and test scores can provide insight into where additional academic assistance is needed*; these assessments must be honest, however, and not artificially inflated. Nearly half of all students in the operating sample had a GPA of 3.01 or higher, suggesting that grade inflation and restriction of range could reduce the predictive power of the variable. Standardized testing places undue pressure on teachers and students, leading to reduction in standards on one side and cheating on the other (Berliner & Nichols, 2005).
2. *Students whose highest mathematics course was general or consumer mathematics were 50% more likely to report taking RM, whereas students whose highest mathematics class was Geometry were 30% more likely*. This suggests policies that require mathematics through Algebra 2 for college bound students, a policy suggestion being worked on by organizations such as Achieve, Inc. and the Bill and Melinda Gates Foundation' College Ready initiative (Achieve, 2010; n.d.). It should be noted, however, that studies such as this cannot establish a causal relationship. Forcing all students to take additional mathematics for high school graduation assumes that the additional courses will cause fewer students to be placed into RM. However the placement test score has a questionable relationship with high school course taking (Hughes & Scott-

> Clayton, 2011) and I have shown that students who take advanced courses (including calculus) still place into remedial mathematics. These findings call into question the causal relationship between additional mathematics courses and a reduction in RM placement.

What is noteworthy is the overwhelmingly small impact that high school variables outside of the strictly academic have on a student's likelihood of taking RM. Many of the strongest theories cannot be tested due to problems of missing data.

Alternative Ways of Considering the Problem

A quantitative look at the problem of mathematics remediation is interesting but insufficient to truly understand the subject. This study can discuss what has happened, but not why it happened, leaving a wide area open for further research.

High school academic indicators provide the easiest early warning system for students who could end up in remedial education; however, elements such as test scores, GPAs, and mathematics courses taken do not explain all of the reasons particular students have reported taking RM. That group included students who had taken courses through Calculus, had GPAs over 3.00, and had test scores that were only marginally lower, on average. As Figure 1 shows, the differences between students who reported taking RM and those who did not on the base-year mathematics test scores were subtle. The means are a mere four points in difference, and some students who reported not taking RM had lower scores than the group that reported taking RM.

The minimal impact of SES cannot be interpreted as SES being unimportant. Between the compressed scale and the composite nature of the variable, the outcome is difficult to interpret clearly. Moreover the literature suggests that the impact of SES may be indirect: SES has been shown to affect all of the academic indicators (Attewell et al., 2006; Riegle-Crumb, 2006) and could, therefore, be indirectly expressed in those indicators. The missing data on many of the attitudinal variables exacerbate the feeling of unease with some of the statistical results. The sample bias found in model 2 makes the model uninterpretable for 73% of traditional college students. This study cannot rule out the impact of attitude for those students, and only better data collection can allow future research to fully understand the impact on RM placement.

If these variables are suggestive but not conclusive, the question remains of what other areas of research could be mined for more concrete answers. One question is the role the placement test plays in sending students to RM. If a student with a high grade on a recent mathematics test can end up in RM, it calls into question either what the placement tests are testing or how the placement test is communicated to students. According to Rosenbaum, Stephen, and Rosenbaum (2010b), 75% of students report not preparing for a placement test, yet nearly three quarters of those students would, in hindsight, advise others to do so. Colleges rarely inform students of the potential effect on such measures as time to degree or financial aid, preferring instead to provide vague, reassuring descriptions of the test and little encouragement for the student to prepare (Rosenbaum, Schuetz, & Foran, 2010a; Rosenbaum, Stephan, & Rosenbaum, 2010b). If sufficient emphasis is not placed on the importance of the placement tests, students may fail to try or properly prepare for the test and may subsequently score poorly enough to be placed in RM.

While Hughes and Scott-Clayton (2011) conclude that the placement tests can accurately predict student performance in college-level coursework, they also concluded that “the placements that result from these tests do not clearly improve student outcomes” (p. 25-26). Given the high drop-out and failure rates of students placed in RM, the question of whether placement is in the best interest of the student should be considered. Some institutions, most often for-profit or highly specialized schools, offer no remedial coursework yet see graduation rates similar to or better than the average community college. Alternative approaches, such as offering the remedial course along side of the college-level course rather than making the remedial course a prerequisite, have shown positive results (Jenkins, Speroni, Belfield, Jagger, & Edgecombe, 2010). By reducing the exit opportunities and providing additional support during college-level work, approaches such as these could improve completion rates while reducing the cost of RM.

The question of attitude remains unanswered. With such a high proportion of the most vulnerable students missing values for the attitude variables, it is unclear what effect might be found or what the interaction of other measures of academic achievement with attitude might be. Negative mathematics self-efficacy cannot be eliminated as an explanation for why students who seemingly perform well on other measures report placement into RM.

Without more complete data, the influence of attitude on RM placement remains an unanswered question. The onus for this lies in the hands of NCES to ensure that sufficient questions are answered to calculate or impute answers to the attitudinal questions. The non-random nature of the missing data makes the attitude variables unusable and calls into question their inclusion in the data set. Future data gathering must focus on, at the very least, on changing the mix of students who fail to answer all the questions so that the missing data will be random.

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Table 1

Response Counts for College Remedial Mathematics Courses

Response	Student Count	Percentage
Valid response (Yes or No)	10,354	63.93%
Legitimate Exclusion	3,979	24.57%
Missing	173	1.07%
Non-respondent	1,864	10.44%
TOTAL	16,197	100.00%

Table 2

Demographic and Family Situation Variables (Collected at the Student-level)

Variable	Description	Collection	% Missing
BYINCOME	Family income	10th Grade	0.00
BYPARED	Parents' highest level of education	10th Grade	4.50
BYRACE	Race/Ethnicity	10th Grade	4.70
BYSES2	SES composite	10th Grade	4.70
BYSEX	Gender of student	10th Grade	4.40
BYSTLANG	English is students native language	10th Grade	4.70

Table 3

High School Transcript and Test Variables (Collected at the Student-level)

Variable	Description	Collection	% Missing
BYGRDRPT	# of grades repeated	10th Grade	13.70
BYS33E	High school remedial math class	10th Grade	11.50
BYTXMSTD	Base-year math test score	10th Grade	1.10
F1HIMATH	Highest math course	Transcript	4.10
F1RGPP2	GPA 9th-12th	Transcript	6.90
F1RHTUNP	Carnegie Units completed	Transcript	6.90
F1RMAT_P	Math units completed	Transcript	6.90
F1S17A	Years of general math	Transcript	5.10
F1S17B	Years of pre-algebra	Transcript	5.10
F1S17C	Years of Algebra1	Transcript	4.60
F1S17D	Years of Geometry	Transcript	4.40
F1S17E	Years of Algebra2	Transcript	4.60
F1S17F	Years of trigonometry	Transcript	5.20
F1S17G	Years of pre-calculus	Transcript	5.10
F1S17H	Years of calculus	Transcript	5.60
F1TXMSTD	First follow up math test score	12th Grade	7.60
F2PSEEXM	Took college entrance exams	College	0,00

Table 4

Mathematics Self-efficacy Variables (Collected at the Student-level)

Variable	Description	Collection	% Missing
BYMATHSE	Math self-efficacy	10th Grade	31.40
BYP58A	Parents: individuals can learn math	10th Grade	18.40
BYP58B	Parents: born with math ability	10th Grade	19.30
BYS88A	Most individuals good at math	10th Grade	24.50
BYS88B	Must be born good at math	10th Grade	24.10
BYS89A	Can do excellent on math tests	10th Grade	25.60
BYS89B	Can learn difficult math texts	10th Grade	25.40
BYS89L	Can understand difficult math	10th Grade	27.80
BYS89R	Can do excellent on math assign.	10th Grade	29.20
BYS89U	Can master math class skills	10th Grade	30.10
F1S18A	Can do excellent on math tests	12th Grade	26.60
F1S18B	Can understand difficult math texts	12th Grade	26.70
F1S18C	Can understand difficult math class	12th Grade	26.80
F1S18D	Can do excellent math assignments	12th Grade	26.90
F1S18E	Can master math class skills	12th Grade	26.80

Table 5

Control Expectation Variables (Collected at the Student-level)

Variable	Description	Collection	% Missing
BYCONEXP	Control expectation	10th Grade	31.80
BYS89E	Can learn something hard	10th Grade	27.10
BYS89N	Can get no bad grades	10th Grade	28.20
BYS89Q	Can get no problems wrong	10th Grade	29.50
BYS89T	Can learn if wants	10th Grade	29.90

Table 6

Educational Expectation Variables (Collected at the Student-level)

Variable	Description	Collection	% Missing
BYPARASP	Parent: educational aspirations	10th Grade	0.80
BYSTEXP	Student educational expectation	10th Grade	4.70
BYTM20	Teacher expectations	10th Grade	23.60
F1STEXP	Student: Postsecondary plans	12th Grade	3.60

Table 7

Instrumental Motivation Variables (Collected at the Student-level)

Variable	Description	Collection	% Missing
BYINSTMO	Instrumental motivation	10th Grade	30.20
BYS37	Important to get good grades	10th Grade	5.90
BYS89D	Studies to get a good grade	10th Grade	25.70
BYS89H	Studies to increase job opportunities	10th Grade	26.70
BYS89P	Studies to ensure financial security	10th Grade	28.00

Table 8

Student Action Control Variables (Collected at the Student-level)

Variable	Description	Collection	% Missing
BYACTCTL	Effort & persistence	10th Grade	31.90
BYS29A	How often reviews math work	10th Grade	9.20
BYS29B	How often listens to lecture	10th Grade	9.70
BYS29C	Copies math notes from board	10th Grade	11.20
BYS29D	How often uses non-textbooks	10th Grade	9.90
BYS29E	How often does problem solving	10th Grade	9.70
BYS29I	Explains math work orally	10th Grade	9.80
BYS29J	Participates in student discussions	10th Grade	9.20
BYS35A	Hrs: math homework in school	10th Grade	11.10
BYS35B	Hrs: math homework out of school	10th Grade	10.50
BYS89G	Remembers most important things	10th Grade	27.30
BYS89J	Works as hard as possible	10th Grade	27.40
BYS89O	Keeps studying difficult material	10th Grade	29.10
BYS89S	Does best to learn	10th Grade	30.10
BYS89V	Gives best effort when studying	10th Grade	29.80
BYSTPREP	Class preparation level	10th Grade	10.40
BYTM04	Teacher: Student works hard	10th Grade	20.70
BYTM06	Teacher: Exceptionally passive	10th Grade	20.30
BYTM07	Teacher: Talks outside of class	10th Grade	20.10
BYTM10	Teacher: Difficulty of class	10th Grade	19.50
BYTM12	Teacher: Fallen behind in math	10th Grade	20.20
BYTM13	Teacher: Completes homework	10th Grade	20.20
BYTM14	Teacher: Often absent	10th Grade	19.90
BYTM15	Teacher: Often tardy	10th Grade	19.70
BYTM16	Teacher: Student is attentive	10th Grade	20.40
BYTM17	Teacher: Student is disruptive	10th Grade	19.60

Table 9

Technological Resource Variables (Collected at the Student-level)

Variable	Description	Collection	% Missing
BYS29F	Uses calculators in math 2002	10th Grade	9.40
BYS29G	Uses graphing calculators 2002	10th Grade	11.20
BYS29H	Uses computers in math 2002	10th Grade	11.70
BYS32EA	Used computer fall 2000	10th Grade	16.20
BYS32EB	Used computer fall 2001	10th Grade	16.70
BYS32FA	Used computer spring 2001	10th Grade	17.40
BYS32FB	Used computer spring 2002	10th Grade	20.40
F1S19A	Uses calculators in math 2004	12th Grade	26.70
F1S19B	Uses graphing calculators 2004	12th Grade	26.90
F1S19C	Uses computers in math 2004	12th Grade	27.00
F1S20A	Used computer fall 2003	12th Grade	26.90
F1S20B	Used computer spring 2004	12th Grade	27.00
F1S20E	Used computer fall 2002	12th Grade	27.30
F1S20F	Used computer spring 2003	12th Grade	27.30

Table 10

High School or College-level Variables (Collected at the School/College-level)

Variable	Description	Collection	% Missing
BY10FLP	Base School percent free lunch	10th Grade	8.00
BYA32	Must pass test for HS Diploma	10th Grade	13.20
BYACCLIM	Academic climate	10th Grade	17.50
BYREGION	Geographic region	10th Grade	0.00
BYSCENP	Base School Enrolment	10th Grade	15.00
BYSCSAF2	School safety - student report	10th Grade	11.40
BYSCTRL	School control	10th Grade	0.00
BYURBAN	School urbanicity	10th Grade	0.00
F1A07B	Years of math required	12th Grade	19.50
F1A14	Class of 2004 must pass test	12th Grade	19.00
F1SCFLP	F1 School percent free lunch	12th Grade	3.10
F2PS1OUT	College out of state	College	1.95
F2PS1EEX	College entrance exam quartiles	College	10.75
F2PS1SEC	College sector control	College	0.40

Table 11

College Attendance Variables (Collected at the Student-level)

Variable	Description	Collection	% Missing
F2PS1FTP	Enrollment level (part/full time)	College	0.10

Table 12

Frequencies and Percentages of Students by Survey Response Categories

Participation by Survey Round			Frequency	Percentage
Base-year	1st Follow-up	2nd Follow-up		
X	X	X	9510	91.8%
X		X	367	3.5%
	X	X	477	4.6%
		TOTAL:	10354	100.0%

Table 13

Percentages of Students by Remedial Courses and Combinations

Students report taking ...	% of operating sample
... zero remedial courses	60.8
... at least one remedial course	39.2
... only remedial mathematics	30.1
... only remedial writing	25.8
... only remedial reading	19.2
... remedial mathematics and writing	18.3
... remedial mathematics and reading	14.0
... remedial writing and reading	15.9
... remedial courses in all three subjects	12.2

Table 14

Variables Included in the Logistic Regression

Variable	Description	% Missing	Effect Size	Model 1	Model 2
BYCONEXP	Control expectation*	31.8	0.010		X
BYMATHSE	Math self-efficacy*	31.4	0.016		X
BYSES2	SES composite*	4.7	0.012	X	X
BYTM16	Teacher: Student is attentive	20.4	0.104		X
BYTM20	Teacher expectations	23.6	0.161		X
BYTXMSTD	Base-year mathematics test score*	1.1	0.063	X	X
F1MATHSE	F1 mathematics self-efficacy*	38.3	0.027		X
F1RGPP2	GPA 9th-12th	6.9	0.160	X	X
F1STEXP	Student educational expectation	3.6	0.102	X	X
F1TXMSTD	First follow up math test score*	7.6	0.075	X	X
F2PS1EEX	College entrance examination quartiles	10.8	0.166		X
F2PS1SEC	College sector control	0.4	0.165	X	X
XHiMath	High mathematics fully listed	4.1	0.190	X	X
XRACE	Race/Ethnicity	4.7	0.090	X	X

Note. All items significant at $p < .001$. An asterisk (*) denotes continuous variables.

Table 15

Model 1 Results: Select Regession Coefficients, Wald Test, and Odds Ratios (<10% Missing)

Variable Name	*B*	*SE*	Wald	Odds Ratio	%
Socioeconomic Status	-.014	.003	24.845	.986	-1.4
Base-year Mathematics Test Score	-.037	.000	21327.249	.964	-3.6
High School GPA					
GPA 0.00 - 1.00	.697	.025	765.935	2.007	100.7
GPA 1.01 - 1.50	.284	.012	523.723	1.329	32.9
GPA 1.51 - 2.00	-.138	.008	330.867	.871	-12.9
GPA 2.01 - 2.50	.207	.006	1416.257	1.230	23.0
GPA 2.51 - 3.00	.033	.005	48.577	1.034	3.4
GPA 3.01 - 3.50			6712.671		
GPA 3.51 - 4.00	-.226	.005	1871.948	.798	-20.2
First Follow-up Student Educational Expectations					
GED or other equivalency only	-.260	.031	69.952	.771	-22.9
High school graduation only	-.182	.014	166.773	.834	-16.6
Attend or complete two-year college/school	-.072	.006	142.073	.930	-7.0
Attend college, four-year degree incomplete	-.264	.010	726.210	.768	-23.2
Graduate from college			1440.168		
Obtain Master's degree or equivalent	.013	.004	9.224	1.013	1.3
Obtain Ph.D., M.D., or other advanced degree	-.093	.005	299.815	.911	-8.9
Don't know	-.134	.008	283.962	.875	-12.5
Highest Level Mathematics Course					
Pre-algebra, general or consumer math	.177	.011	270.619	1.193	19.3
Algebra 1	-.211	.010	493.367	.810	-19.0
Geometry	.092	.006	243.818	1.097	9.7
Algebra 2			12380.776		
Trigonometry	-.370	.005	4622.008	.691	-30.9
Pre-calculus	-.448	.005	7752.769	.639	-36.1
Calculus	-.398	.006	4110.233	.672	-32.8
Constant	1.337	.014	8847.459	3.810	

Note. GED = General Educational Development test; GPA = Grade point average. All coefficients significant at $p < .001$.

Table 16

Model 2 Results: Select Regression Coefficients, Wald Test, and Odds Ratios of Statistically and Practically Significant Variables

Variable Name	*B*	*SE*	Wald	Odds Ratio	%
Socioeconomic Status	-.090	.005	291.988	.914	-8.6
Base-year Mathematics Test Score	-.037	.001	4434.610	.964	-3.6
High School GPA					
GPA 1.51 - 2.00	.505	.020	613.774	1.657	65.7
GPA 2.01 - 2.50	.008	.012	.411*	1.008	
GPA 2.51 - 3.00	.059	.009	42.705	1.061	6.1
GPA 3.01 - 3.50			1998.242		
GPA 3.51 - 4.00	-.238	.009	750.871	.788	-21.2
Highest Level mathematics Course					
No math course or math course other	.347	.041	70.714	1.414	41.4
Pre-algebra, general or consumer math	.647	.028	521.741	1.909	90.9
Algebra 1	-.055	.033	2.699*	.947	
Geometry	.102	.016	43.164	1.108	10.8
Algebra 2			3814.909		
Trigonometry	-.566	.011	2531.059	.568	-43.2
Pre-calculus	-.313	.009	1170.227	.732	-26.8
Calculus	-.249	.011	513.337	.780	-22.0
How often student is attentive in class (math)					
Never	1.480	.041	1283.782	4.393	339.3
Rarely	-.104	.023	20.333	.901	-9.9
Some of the time	-.124	.011	124.868	.884	-11.6
Most of the time			1526.443		
All of the time	-.056	.007	58.456	.946	-5.4
Base-year Control Expectation	-.112	.005	557.109	.894	-10.6
Base-year Math Self-efficacy	.004	.005	.529*	1.004	
First Follow-up Math Self-efficacy	-.090	.004	457.381	.914	-8.6
Constant	1.529	.034	1980.422	4.614	

Note. $*p < .05$; All other variables significant at $p < .001$.

Table 17

Percentages of Students, by Model, Compared to Operating Sample

Variable Names	Operating Sample	Model 1	Model 2
Race/Ethnicity			
Survey Legitimate Skip	0.3		
Missing	3.6		
U.S. Indian/Alaska Native	0.6	0.5*	0.3*
Asian, Hawaii/Pacific Islander	10.3	9.9*	9.8*
Black or African U.S.	11.4	11.0*	0.7*
Hispanic	11.4	10.3*	8.4*
Multi-racial	4.3	4.4*	3.8*
White	58.6	63.9*	71.1*
High School GPA			
Missing	0.0		
Non-respondent	6.9		
GPA 0.00 - 1.00	0.4	0.3*	0.0*
GPA 1.01 - 1.50	1.6	1.4*	0.4*
GPA 1.51 - 2.00	6.2	6.1*	2.5*
GPA 2.01 - 2.50	14.8	15.3*	10.0*
GPA 2.51 - 3.00	22.0	23.3*	19.9*
GPA 3.01 - 3.50	25.2	27.5*	29.5*
GPA 3.51 - 4.00	23.2	26.1*	37.7*
Highest Level mathematics Course			
Missing	0.5		
Survey legitimate skip	0.2		
Non-respondent	3.4		
No math course or math course other	0.5		0.3*
Pre-algebra, general or consumer math	1.9	1.8	0.8*
Algebra 1	3.0	2.7	0.9*
Geometry	8.3	8.1	3.5*
Algebra 2	27.2	28.2	22.1*
Trigonometry	14.4	14.7	13.6*
Pre-calculus	21.7	23.1	28.0*
Calculus	19.3	21.0	30.7*
Sector of First Postsecondary Institution			
Missing	0.4		
Public, four-year or above	39.9	41.2*	49.9*
Private not-for-profit, four-year or above	20.3	21.3*	26.0*
Private for-profit, four-year or above	1.7	1.5*	0.4*
Public, two-year	33.0	31.7*	22.7*
Private not-for-profit, two-year	0.4	0.4	0.4
Private for-profit, two-year	1.8	1.5*	0.4*
Public, less than two-year	1.1	0.8*	
Private not-for-profit, less than two-year	0.2	0.2	
Private for-profit, less than two-year	1.6	1.4*	0.2*
College entrance exam score average scores			
Missing	10.8		
School has open admission policy	37.3		26.2*
Scores are in lowest quartile	7.9		9.1*
Scores are in middle two quartiles	24.7		33.2*
Scores are in highest quartile	19.6		31.5*
Total students	10242	8422	2757

Note. *$p < .001$. Effect size exceeds threshold.

Table 18

Mean Values of Continuous Variables, by Model

	Operating Sample	Model 1	Model 2
Math test standardized score	53.38	53.96*	56.80*
Socioeconomic status composite	0.28	0.29*	0.38*
Base-year mathematics self-efficacy	0.35	0.37*	0.56*
Control expectation scale	0.44	0.45*	0.51*
First follow-up mathematics self-efficacy	0.35	0.36*	0.43*

Note. *p < .001. Effect size exceeds threshold.

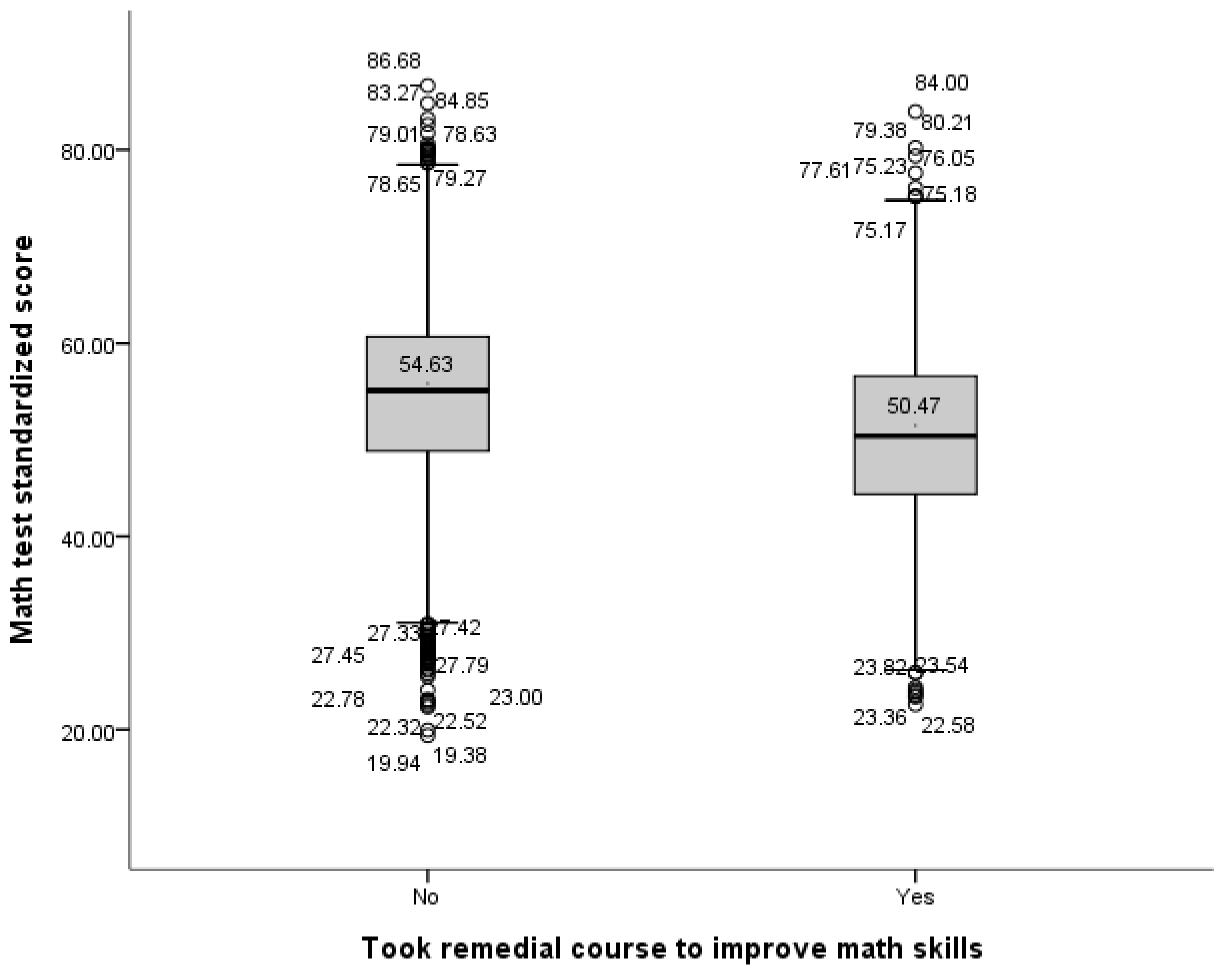

Figure 1. Comparison of base-year math test score for those who did and did not take remedial mathematics.

APPENDIX A

KEY VARIABLE LIST, INCLUDING SOURCE AND QUESTION DETAILS

Variable	Description	% Missing	Variable Type	Source	Variable Details
BYCONEXP	Control Expectation	31.80	Continuous (z-score)	Composite of self-report items	This variable is a scale of the respondent's success expectations in the base-year. Higher values represent greater expectations of success in academic learning. Variable was created through principal factor analysis (weighted by BYSTUWT) and standardized to a mean of 0 and standard deviation of 1. Only respondents who provided a full set of responses were assigned a scale value. The coefficient of reliability (alpha) for the scale is 0.84. The questions used to calculate the variable were: BYS89E: When I sit myself down to learn something really hard, I can learn it BYS89N: If I decide not to get any bad grades, I can really do it BYS89Q: If I decide not to get any problems wrong, I can really do it BYS89T: If I want to learn something well, I can
BYMATHSE	Math self-efficacy	31.40	Continuous (z-score)	Composite of self-report items	This variable is a scale of the respondent's self-efficacy in math in the base-year. Higher values represent greater self-efficacy. Variable was created through principal factor analysis weighted by BYSTUWT) and standardized to a mean of 0 and standard deviation of 1. Only respondents who provided a full set of responses were assigned a scale value. The coefficient of reliability (alpha) for the scale is 0.93. The questions used to calculate the variable were: BYS89A: I'm confident that I can do an excellent job on my math tests BYS89B: I'm certain I can understand the most difficult material BYS89L: I'm confident I can understand the most complex math material BYS89R: I'm confident I can do an excellent job on my math assignments BYS89U: I'm certain I can master the skills being taught in my math class
BYRACE: revised to XRACE	Race/Ethnicity	4.70	Categorical	Self-report, Derived	U.S. Indian or Alaska Native Asian, Hawaiian or other Pacific Islander Black, not Hispanic or Latino Hispanic More than one race, non-Hispanic White, not Hispanic or Latino Derived version combined Hispanic students regardless of whether they defined an ethnicity or not.
BYSES2	SES composite	4.70	Continuous (z-score)	Composite of self-report	Socioeconomic status. Composite of Mother and Father's occupation, Mother and Father's education, Family Income. Uses 1989 GSS Occupational Prestige scores. Each item is converted to a z-score. The z-scores are then averaged, yielding a scale of 2.11 to -1.98

Variable	Description	% Missing	Variable Type	Source	Variable Details
BYTM16	Teacher: Student is Attentive	20.40	Categorical	Teacher Survey	How often is this student attentive in your class? Never, Rarely, Some of the time, Most of the time, All of the time Don't Know
BYTM20	Teacher expectations	23.60	Categorical	Teacher Survey	How far in school do you expect this student to get? Less than high school graduation only HS graduation or GED only Will attend or complete a two-year school or college Will go to college but not complete a four-year degree Will graduate from college Will obtain a Master's degree or equivalent Will obtain a PhD, professional or other advanced degree Don't Know
BYTXMSTD	Base-year math test score	1.10	Continuous	Test score	Math Standardized Test Score
F1HIMATH: revised to XHIMATH	Highest math course	4.10	Categorical	Self-report / Derived	Highest math course of a half year or more from F1S17A - F1S17 J. Calculus Pre-calculus Trigonometry Algebra 2 Geometry Algebra I Pre-algebra, general or consumer math Other math coursework or none
F1MATHSE	F1 mathematics self-efficacy	38.3	Continuous (z-score)	Composite of self-report items	This variable is a scale of the respondent’s self-efficacy in math in the first follow-up. Higher values represent greater self-efficacy. Variable was created through principal factor analysis (weighted by F1QWT) and standardized to a mean of 0 and standard deviation of 1. Only respondents who provided a full set of responses were assigned a scale value. The coefficient of reliability (alpha) for the scale is 0.91.

Variable	Description	% Missing	Variable Type	Source	Variable Details
F1RGPP2	GPA 9th-12th	6.90	Categorical	Transcript	GPA for all courses taken in the 9th - 12th grades 0.00 - 1.00 1.01 - 1.50 1.51 - 2.00 2.01 - 2.50 2.51 - 3.00 3.01 - 3.50 3.51 - 4.00
F1STEXP	First follow-up student educational expectations	3.60	Categorical	Self-report	How far in school respondent thinks he/she will get. Less than high school graduation only GED or other equivalency HS graduation only Will attend/complete a two-year school college/school Will go to college but not complete a four-year degree Will graduate from college Will obtain a Master's degree or equivalent Will obtain a PhD, professional degree or other advanced degree Don't Know
F1TXMSTD	First follow up math test score	7.60	Continuous	Test score	Math Standardized Test Score
F2PS1EEX	College entrance exam quartiles	10.75	Categorical	Self-report of school. IPEDS, SAT, ACT quartiles	College entrance exam scores relative to average No postsecondary attendance 1st PS school has open admission policy Scores are in the lowest quartile Scores are in the middle two quartiles Scores are in the highest quartile
F2PS1SEC	College sector control	0.40	Categorical	Self-report of school, IPEDS	Sector of first postsecondary institution Public four-year or above Private not-for-profit four-year or above Private for-profit four-year or above Public two-year Private not-for-profit two-year Private for-profit two-year Public less than two-year Private not-for-profit less than two-year Private for-profit less than two-year

APPENDIX B

COMPLETE VARIABLE LIST

Group	Variable	Description	%Missing	Test Value	df	Weighted ES
Demographic	BYINCOME	Family income	0.00	14121.779	12	0.078
Demographic	BYPARED	Parents' highest level of education	4.50	13788.075	7	0.079
Demographic	BYRACE	Race/Ethnicity	4.70	17569.242	6	0.090
Demographic	BYSES2	SES composite	4.70	120.418	1217004	0.012
Demographic	BYSEX	Gender of student	4.40	403.296	1	0.014
Demographic	BYSTLANG	English is students native language	4.70	7128.231	1	0.057
Transcript	BYGRDRPT	# of grades repeated	13.70	11520.911	5	0.071
Transcript	BYS33E	High school remedial math class	11.50	9967.991	1	0.070
Transcript	BYTXMSTD	Base-year math test score	1.10	305.094	1386051	0.063
Transcript	F1HIMATH	Highest math course	4.10	73708.571	6	0.182
Transcript	F1RGPP2	GPA 9th-12th	6.90	55430.436	6	0.160
Transcript	F1RHTUNP	Carnegie Units completed	6.90	11961.772	28	0.075
Transcript	F1RMAT_P	Math units completed	6.90	15791.269	6	0.086
Transcript	F1S17A	Years of general math	5.10	14168.469	3	0.080
Transcript	F1S17B	Years of pre-algebra	5.10	23662.730	3	0.104
Transcript	F1S17C	Years of Algebra1	4.60	24879.214	3	0.106
Transcript	F1S17D	Years of Geometry	4.40	7404.025	3	0.058
Transcript	F1S17E	Years of Algebra2	4.60	20037.029	3	0.095
Transcript	F1S17F	Years of trigonometry	5.20	35304.512	3	0.127
Transcript	F1S17G	Years of pre-calculus	5.10	52171.387	3	0.154
Transcript	F1S17H	Years of calculus	5.60	30522.678	3	0.118
Transcript	F1TXMSTD	First follow up math test score	7.60	317.494	1248676	0.075
Transcript	XEntExm	Took any college entrance exam	0,00	19870.357	1	0.093
Transcript	XMathGain	F1TXMSTD - BYTXMSTD	7.90	31.778	675534	0.001
Math self-efficacy	BYMATHSE	Math self-efficacy	31.40	115.216	796872	0.016
Math self-efficacy	BYP58A	Parents: individuals can learn math	18.40	269.138	3	0.012
Math self-efficacy	BYP58B	Parents: born with math ability	19.30	1084.079	3	0.024
Math self-efficacy	BYS88A	Most individuals good at math	24.50	1972.583	3	0.034
Math self-efficacy	BYS88B	Must be born good at math	24.10	1475.172	3	0.029
Math self-efficacy	BYS89A	Can do excellent on math tests	25.60	12874.866	3	0.087
Math self-efficacy	BYS89B	Can learn difficult math texts	25.40	12202.403	3	0.084
Math self-efficacy	BYS89L	Can understand difficult math	27.80	11134.266	3	0.082
Math self-efficacy	BYS89R	Can do excellent on math assign.	29.20	13938.689	3	0.092
Math self-efficacy	BYS89U	Can master math class skills	30.10	12213.357	3	0.087
Math self-efficacy	F1S18A	Can do excellent on math tests	26.60	15865.350	3	0.098
Math self-efficacy	F1S18B	Can understand difficult math texts	26.70	19449.774	3	0.109

Group	Variable	Description	%Missing	Test Value	df	Weighted ES
Math self-efficacy	F1S18C	Can understand difficult math class	26.80	18971.157	3	0.107
Math self-efficacy	F1S18D	Can do excellent math assignments	26.90	17935.670	3	0.105
Math self-efficacy	F1S18E	Can master math class skills	26.80	23435.726	3	0.119
Control Expectation	BYCONEXP	Control expectation	31.80	83.412	701339	0.010
Control Expectation	BYS89E	Can learn something hard	27.10	12338.829	3	0.086
Control Expectation	BYS89N	Can get no bad grades	28.20	11649.625	3	0.084
Control Expectation	BYS89Q	Can get no problems wrong	29.50	3514.034	3	0.046
Control Expectation	BYS89T	Can learn if wants	29.90	10870.358	3	0.082
Expectations	BYPARASP	Parent: educational aspirations	0.80	6648.994	6	0.054
Expectations	BYSTEXP	Student educational expectation	4.70	14771.193	6	0.086
Expectations	BYTM19	Teacher: Recommended for AP	28.20	20103.640	1	0.111
Expectations	BYTM20	Teacher expectations	23.60	44464.871	6	0.161
Expectations	F1STEXP	Student educational expectation	3.60	22154.653	5	0.102
Instrumental Motiv.	BYINSTMO	Instrumental motivation	30.20	50.417	862025	0.003
Instrumental Motiv.	BYS37	Important to get good grades	5.90	6403.854	3	0.055
Instrumental Motiv.	BYS89D	Studies to get a good grade	25.70	4613.121	3	0.052
Instrumental Motiv.	BYS89H	Studies to increase job opportunities	26.70	2507.700	3	0.039
Instrumental Motiv.	BYS89P	Studies to ensure financial security	28.00	2692.016	3	0.040
Action Control	BYACTCTL	Effort & persistence	31.90	32.346	1316170	0.001
Action Control	BYS29A	How often reviews math work	9.20	10771.360	4	0.072
Action Control	BYS29B	How often listens to lecture	9.70	2445.705	4	0.034
Action Control	BYS29C	Copies math notes from board	11.20	1042.400	4	0.023
Action Control	BYS29D	How often uses non-textbooks	9.90	11781.917	4	0.076
Action Control	BYS29E	How often does problem solving	9.70	840.925	4	0.020
Action Control	BYS29I	Explains math work orally	9.80	2236.056	4	0.033
Action Control	BYS29J	Participates in student discussions	9.20	4597.037	4	0.047
Action Control	BYS35A	Hrs: math homework in school	11.10	5572.436	20	0.053
Action Control	BYS35B	Hrs: math homework out of school	10.50	9327.406	20	0.068
Action Control	BYS89G	Remembers most important things	27.30	8266.899	3	0.070
Action Control	BYS89J	Works as hard as possible	27.40	2587.914	3	0.039
Action Control	BYS89O	Keeps studying difficult material	29.10	5907.277	3	0.060
Action Control	BYS89S	Does best to learn	30.10	4070.494	3	0.050
Action Control	BYS89V	Gives best effort when studying	29.80	1173.028	3	0.027
Action Control	BYSTPREP	Class preparation level	10.40	18.414	977865	0.000
Action Control	BYTM04	Teacher: Student works hard	20.70	6584.544	1	0.061
Action Control	BYTM06	Teacher: Exceptionally passive	20.30	1836.424	1	0.032
Action Control	BYTM07	Teacher: Talks outside of class	20.10	9.609	1	0.002
Action Control	BYTM10	Teacher: Difficulty of class	19.50	7095.531	2	0.063
Action Control	BYTM12	Teacher: Fallen behind in math	20.20	6881.987	1	0.062
Action Control	BYTM13	Teacher: Completes homework	20.20	9003.067	4	0.071

Group	Variable	Description	%Missing	Test Value	df	Weighted ES
Action Control	BYTM14	Teacher: Often absent	19.90	4644.157	4	0.051
Action Control	BYTM15	Teacher: Often tardy	19.70	5594.211	4	0.056
Action Control	BYTM16	Teacher: Student is attentive	20.40	19273.031	4	0.104
Action Control	BYTM17	Teacher: Student is disruptive	19.60	4296.275	4	0.049
Technology	BYS29F	Uses calculators in math 2002	9.40	6025.216	4	0.054
Technology	BYS29G	Uses graphing calculators 2002	11.20	5310.656	4	0.051
Technology	BYS29H	Uses computers in math 2002	11.70	7726.023	4	0.062
Technology	BYS32EA	Used computer fall 2000	16.20	53.902	1	0.005
Technology	BYS32EB	Used computer fall 2001	16.70	10.002	1	0.002
Technology	BYS32FA	Used computer spring 2001	17.40	1399.839	1	0.027
Technology	BYS32FB	Used computer spring 2002	20.40	681.676	1	0.019
Technology	F1S19A	Uses calculators in math 2004	26.70	2945.956	4	0.042
Technology	F1S19B	Uses graphing calculators 2004	26.90	7032.173	4	0.066
Technology	F1S19C	Uses computers in math 2004	27.00	3315.920	4	0.045
Technology	F1S20A	Used computer fall 2003	26.90	3013.268	2	0.043
Technology	F1S20B	Used computer spring 2004	27.00	3397.040	2	0.046
Technology	F1S20E	Used computer fall 2002	27.30	293.179	2	0.013
Technology	F1S20F	Used computer spring 2003	27.30	1208.724	2	0.027
School	BY10FLP	Base School percent free lunch	8.00	6409.087	6	0.055
School	BYA32	Must pass test for HS Diploma	13.20	2507.322	1	0.035
School	BYACCLIM	Academic climate	17.50	52.850	1110187	0.003
School	BYREGION	Geographic region	0.00	2775.155	3	0.035
School	BYSCENP	Base School Enrolment	15.00	3756.520	8	0.044
School	BYSCSAF2	School safety - student report	11.40	41.458	955593	0.002
School	BYSCTRL	School control	0.00	2402.234	2	0.032
School	BYURBAN	School urbanicity	0.00	2696.586	2	0.034
School	F1A07B	Years of math required	19.50	5338.280	3	0.054
School	F1A14	Class of 2004 must pass test	19.00	958.784	1	0.023
School	F1SCFLP	F1 School percent free lunch	3.10	4121.101	6	0.048
School	F2PS1EEX	College entrance exam quartiles	10.75	56351.568	3	0.166
School	F2PS1OUT	College out of state	1.95	9044.690	1	0.063
School	F2PS1SEC	College sector control	0.40	62870.444	8	0.165
College	F2PS1FTP	Enrollment level (part/full time)	0.10	9824.890	2	0.065

Note. All variables significant at $p < .001$ when weighted.

APPENDIX C

COMPLETE LOGISTIC REGRESSION TABLES

MODEL 1: Variable Name	Frequency	% of cases	*B*	*SE*	Wald	Odds Ratio	% effect
Race/Ethnicity							
U.S. Indian/Alaska Native	44	0.5	-0.234	0.02	142.638	0.791	-20.9
Asian, Hawaii/Pacific Islander	832	9.9	0.301	0.008	1308.533	1.351	35.1
Black or African U.S.	924	11.0	-0.255	0.006	1988.344	0.775	-22.5
Hispanic	870	10.3	0.144	0.006	677.334	1.155	15.5
Multi-racial	368	4.4	-0.371	0.009	1625.927	0.69	-31
White	5384	63.9			6554.599		
Socioeconomic Status	8422	100	-0.014	0.003	24.845	0.986	-1.4
			8422				
Base-year Mathematics Test Score	8422	100	-0.037	0	21327.249	0.964	-3.6
High School GPA							
GPA 0.00 - 1.00	22	0.3	0.697	0.025	765.935	2.007	100.7
GPA 1.01 - 1.50	122	1.4	0.284	0.012	523.723	1.329	32.9
GPA 1.51 - 2.00	513	6.1	-0.138	0.008	330.867	0.871	-12.9
GPA 2.01 - 2.50	1287	15.3	0.207	0.006	1416.257	1.23	23
GPA 2.51 - 3.00	1961	23.3	0.033	0.005	48.577	1.034	3.4
GPA 3.01 - 3.50	2317	27.5			6712.671		
GPA 3.51 - 4.00	2200	26.1	-0.226	0.005	1871.948	0.798	-20.2
First Follow-up Student Educational Expectations							
GED or other equivalency only	17	0.2	-0.26	0.031	69.952	0.771	-22.9
High school graduation only	105	1.2	-0.182	0.014	166.773	0.834	-16.6
Attend or complete two-year college/school	726	8.6	-0.072	0.006	142.073	0.93	-7
Attend college, four-year degree incomplete	213	2.5	-0.264	0.01	726.21	0.768	-23.2
Graduate from college	3105	36.9			1440.168		
Obtain Master's degree or equivalent	2344	27.8	0.013	0.004	9.224	1.013	1.3
Obtain PhD, MD, or other advanced degree	1515	18.0	-0.093	0.005	299.815	0.911	-8.9
Don't know	395	4.7	-0.134	0.008	283.962	0.875	-12.5
Highest Level Mathematics Course							
Pre-algebra, general or consumer math	148	1.8	0.177	0.011	270.619	1.193	19.3
Algebra 1	231	2.7	-0.211	0.01	493.367	0.81	-19
Geometry	682	8.1	0.092	0.006	243.818	1.097	9.7
Algebra 2	2375	28.2			12380.776		
Trigonometry	1239	14.7	-0.37	0.005	4622.008	0.691	-30.9
Pre-calculus	1942	23.1	-0.448	0.005	7752.769	0.639	-36.1
Calculus	1766	21.0	-0.398	0.006	4110.233	0.672	-32.8
Sector of First Postsecondary Institution							

MODEL 1: Variable Name	Frequency	% of cases	*B*	*SE*	Wald	Odds Ratio	% effect
Public, four-year or above	3471	41.2			18176.952		
Private not-for-profit, four-year or above	1798	21.3	-0.14	0.005	759.597	0.869	-13.1
Private for-profit, four-year or above	129	1.5	-0.258	0.012	431.629	0.773	-22.7
Public, two-year	2670	31.7	0.146	0.004	1118.728	1.157	15.7
Private not-for-profit, two-year	33	0.4	-1.551	0.036	1856.566	0.212	-78.8
Private for-profit, two-year	124	1.5	-0.748	0.013	3077.276	0.473	-52.7
Public, less than two-year	67	0.8	-0.352	0.017	450.582	0.704	-29.6
Private not-for-profit, less than two-year	14	0.2	-0.956	0.058	272.069	0.384	-61.6
Private for-profit, less than two-year	116	1.4	-1.567	0.019	7145.698	0.209	-79.1
Constant	8422		1.337	0.014	8847.459	3.81	

MODEL 2: Variable Name	Frequency	% of cases	B	S.E.	Wald	Odds Ratio	% effect
Race/Ethnicity							
U.S. Indian/Alaska Native	7	0.3	-1.193	0.061	386.362	0.303	-69.70%
Asian, Hawaii/Pacific Islander	271	9.8	0.109	0.016	46.937	1.115	11.50%
Black or African U.S.	18	0.7	-0.135	0.013	106.616	0.873	-12.70%
Hispanic	231	8.4	-0.264	0.012	472.576	0.768	-23.20%
Multi-racial	104	3.8	-0.123	0.018	46.414	0.884	-11.60%
White	1961	71.1			965.954		
Socioeconomic Status	2757	100.0	-0.09	0.005	291.988	0.914	-8.60%
Base-year Mathematics Test Score	2757	100.0	-0.037	0.001	4434.61	0.964	-3.60%
High School GPA							
GPA 0.00 - 1.00	*1*	0.0	*7.525*	*1.994*	*14.24*	*1853.124*	
GPA 1.01 - 1.50	11	0.4	-1.018	0.067	232.74	0.361	-63.90%
GPA 1.51 - 2.00	68	2.5	0.505	0.02	613.774	1.657	65.70%
GPA 2.01 - 2.50	*275*	10.0	*0.008*	*0.012*	*0.411*	*1.008*	
GPA 2.51 - 3.00	549	19.9	0.059	0.009	42.705	1.061	6.10%
GPA 3.01 - 3.50	813	29.5			1998.242		
GPA 3.51 - 4.00	1040	37.7	-0.238	0.009	750.871	0.788	-21.20%
First Follow-up Student Educational Expectations							
GED or other equivalency only	3	0.1	0.335	0.073	21.169	1.399	39.90%
High school graduation only	14	0.5	0.35	0.035	99.682	1.419	41.90%
Attend or complete two-year college/school	124	4.5	-0.353	0.015	520.846	0.703	-29.70%
Attend college, four-year degree incomplete	35	1.3	-0.392	0.025	245.594	0.676	-32.40%
Graduate from college	1001	36.3			1784.201		

MODEL 2: Variable Name	Frequency	% of cases	B	S.E.	Wald	Odds Ratio	% effect
Obtain Master's degree or equivalent	871	31.6	0.183	0.008	539.643	1.2	20.00%
Obtain PhD, MD, or other advanced degree	*629*	22.8	*-0.008*	*0.009*	*0.794*	*0.992*	
Don't know	79	2.9	-0.132	0.019	45.895	0.877	-12.30%
Highest Level mathematics Course							
No math course or math course other	9	0.3	0.347	0.041	70.714	1.414	41.40%
Pre-algebra, general or consumer math	22	0.8	0.647	0.028	521.741	1.909	90.90%
Algebra 1	*26*	0.9	*-0.055*	*0.033*	*2.699*	*0.947*	
Geometry	97	3.5	0.102	0.016	43.164	1.108	10.80%
Algebra 2	610	22.1			3814.909		
Trigonometry	374	13.6	-0.566	0.011	2531.059	0.568	-43.20%
Pre-calculus	773	28.0	-0.313	0.009	1170.227	0.732	-26.80%
Calculus	846	30.7	-0.249	0.011	513.337	0.78	-22.00%
Sector of First Postsecondary Institution							
Public, four-year or above	1377	49.9			1554.37		
Private not-for-profit, four-year or above	716	26.0	-0.265	0.009	953.797	0.767	-23.30%
Private for-profit, four-year or above	11	0.4	0.191	0.036	27.982	1.211	21.10%
Public, two-year	626	22.7	-0.164	0.016	111.362	0.849	-15.10%
Private not-for-profit, two-year	10	0.4	-2.067	0.104	392.877	0.127	-87.30%
Private for-profit, two-year	11	0.4	-0.426	0.043	98.984	0.653	-34.70%
Private for-profit, less than two-year	6	0.2	-7.089	0.932	57.826	0.001	-99.90%
How far math teacher expects student to get in school							
Less than high school graduation	3	0.1	-0.753	0.097	60.866	0.471	-52.90%
High school graduation or GED only	95	3.4	-0.361	0.019	375.527	0.697	-30.30%
Attend or complete two-year college/school	228	8.3	0.187	0.012	260.847	1.205	20.50%
Attend college, four-year degree incomplete	172	6.2	-0.202	0.013	242.201	0.817	-18.30%
Graduate from college	1526	55.4			1981.151		
Obtain Master's degree or equivalent	568	20.6	-0.092	0.009	94.933	0.912	-8.80%
Obtain PhD, MD, other advanced degree	165	6.0	-0.578	0.021	735.908	0.561	-43.90%
How often student is attentive in class (math)							
Never	14	0.5	1.48	0.041	1283.782	4.393	339.30%
Rarely	53	1.9	-0.104	0.023	20.333	0.901	-9.90%
Some of the time	277	10.0	-0.124	0.011	124.868	0.884	-11.60%
Most of the time	1218	44.2			1526.443		
All of the time	1195	43.3	-0.056	0.007	58.456	0.946	-5.40%
College entrance exam score average scores							
School has open admission policy	722	26.2			847.993		

MODEL 2: Variable Name	Frequency	% of cases	B	S.E.	Wald	Odds Ratio	% effect
Scores are in lowest quartile	252	9.1	0.215	0.018	149.03	1.239	23.90%
Scores are in middle two quartiles	914	33.2	0.075	0.016	23.323	1.078	7.80%
Scores are in highest quartile	869	31.5	-0.128	0.016	62.819	0.879	-12.10%
Base-year Control Expectation	2757	100.0	-0.112	0.005	557.109	0.894	-10.60%
Base-year Math Self-efficacy	*2757*	100.0	*0.004*	*0.005*	*0.529*	*1.004*	
First Follow-up Math Self-efficacy	2757	100.0	-0.09	0.004	457.381	0.914	-8.60%
Constant	2757		1.529	0.034	1980.422	4.614	

Note. Italicized variables are not significant. All other variables significant at $p < .001$.