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An Implementation and Early Impacts Report

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Overview

Many incoming college students are referred to remedial programs in math or English based on scores they earn on standardized placement tests. Yet research shows that some students assigned to remediation based on test scores would likely succeed in a college-level course in the same subject area without first taking a remedial course if given that opportunity. Research also suggests that other measures of student skills and performance, and in particular high school grade point average (GPA), may be useful in assessing college readiness.

CAPR is conducting a random assignment study of a multiple measures placement system based on data analytics to determine whether it yields placement determinations that lead to better student outcomes than a system based on test scores alone. Seven community colleges in the State University of New York (SUNY) system are participating in the study. The alternative placement system we evaluate uses data on prior students to weight multiple measures — including both placement test scores and high school GPAs — in predictive algorithms developed at each college that are then used to place incoming students into remedial or college-level courses. Over 13,000 incoming students who arrived at these colleges in the fall 2016, spring 2017, and fall 2017 terms were randomly assigned to be placed using either the status quo placement system (the control group) or the alternative placement system (the program group). The three cohorts of students will be tracked through the fall 2018 term, resulting in the collection of three to five semesters of outcomes data, depending on the cohort.

This interim report, the first of two, examines implementation of the alternative placement system at the colleges and presents results on first-term impacts for 4,729 students in the fall 2016 cohort. The initial results are promising. The early findings show that:

- While implementing the alternative system was more complex than expected, every college developed the procedures that were required to make it work as intended.

- Many program group students were placed differently than they would have been under the status quo placement system. In math, 14 percent of program group students placed higher than they would have under a test-only system (i.e., in college-level), while 7 percent placed lower (i.e., in remedial). In English, 41.5 percent placed higher, while 6.5 percent placed lower.

- Program group students were 3.1 and 12.5 percentage points more likely than control group students to both enroll in and complete (with a grade of C or higher) a college-level math or English course in the first term.

(Enrollment and completion rates among the control group were 14.1 percent in math and 27.2 percent in English.)

- Women appeared to benefit more than men from program group status in math on college-level math course placement, enrollment, and completion (with a grade of C or higher) outcomes; Black and Hispanic students appeared to benefit more than White students from program group status in English on college-level English course placement and enrollment outcomes, but not on completion (with a grade of C or higher).
- Implementation of the alternative system added roughly $110 per student to status quo fall-term costs for testing and placing students at the colleges; ongoing costs in the subsequent fall term were roughly $40 per student above status quo costs.

The final report, to be released in 2019, will examine a range of student outcomes for all three cohorts, including completion of introductory college-level courses, persistence, and the accumulation of college credits over the long term.

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Executive Summary

Two thirds of students who attend community colleges and two fifths of students who attend public four-year colleges enroll in one or more remedial courses (also known as developmental education courses) to strengthen their skills for college-level coursework (Chen, 2016). Remedial courses may be helpful to some students, but they also require students to make a substantial investment of limited time and money that could otherwise be applied to college-level coursework, and studies suggest that the effects of remedial courses on student outcomes are at best mixed for those who are thought to be on the cusp of needing additional academic support (Jaggars & Stacey, 2014). Further, students who start college in remedial coursework are less likely to graduate (Attewell, Lavin, Domina, & Levey, 2006). It is therefore important to decide which incoming students ought to enroll in remedial courses.

Currently, most students who participate in remediation in math or English (or both) are referred to these programs based on the scores they earn on standardized placement tests, which they typically take when they arrive at college. Yet in recent years, questions have arisen about how useful these standardized tests are for placing incoming students into remedial and college-level coursework. Research shows that some students assigned to remediation based on test scores would likely pass a college-level course in the same subject area without first taking a remedial course if given that opportunity; it also suggests that using multiple measures of student skills and performance, and in particular high school grade point average (GPA), may be useful in assessing college readiness (Belfield & Crosta, 2012; Scott-Clayton, 2012).

Partly in response to these findings, an increasing number of colleges are now exploring or beginning to use multiple measures to place incoming students into remedial or college-level courses (Rutschow & Mayer, 2018). Multiple measures placement systems often make use of placement test results but also consider other relevant data on incoming students, such as high school GPA. While studies suggest that using multiple measures may result in the improved placement of students into remedial and college-level courses, little evidence to date has shown that using a multiple measures placement system influences other student outcomes.

To address this gap, CAPR is conducting a random assignment study of a multiple measures placement system to determine whether it yields placement determinations that lead to better student outcomes than a system based on test scores alone. Seven community colleges in the State University of New York (SUNY) system are participating in the study. The placement system CAPR researchers are evaluating uses data on prior students to develop predictive algorithms at each college to weight multiple measures — including placement test scores, high school GPA, years since high school graduation, and in some cases other measures — that are then used to place incoming students into remedial or college-level courses. Over 13,000 incoming students who arrived at these colleges in the fall 2016, spring 2017, and fall 2017 terms were randomly assigned to be placed using either the status quo placement system (the control group) or the alternative placement system (the program group). The three cohorts of students will be tracked through the fall 2018 term, resulting in the collection of three to five semesters of outcomes data depending on the cohort.

CAPR researchers and personnel from the seven colleges worked together to develop the data analytics algorithms and the alternative system for placement. Given differences among the SUNY community colleges participating in the study, the data analytics algorithms employed to assess program group students were created for each college individually (one each for math and English), using historical data from 2011–14. Data on multiple measures — such as high school GPA, years since high school graduation, and placement test scores — as well as data on outcomes in college-level courses were used to create algorithms that weight each measure in the most appropriate way for predicting student performance in initial college-level math and English courses.

After the algorithms were developed, historical data were also used to predict placement and success rates in initial college-level courses in each subject area at a range of cut points. Faculty at each college then created placement rules by choosing the cut points that would be used to place program group students into remedial or college-level math and English courses.

Development of the algorithms using historical data showed that placement accuracy is a concern for all colleges in the study. Between one third and one half of prior students were estimated to have been "misplaced" in math and English at the colleges. Misplaced students include "underplaced" students, who were placed in a remedial course but would likely have been able to complete an initial college-level course with a grade of C or higher, as well as "overplaced" students, who were placed into and failed a college-level course. With one exception (math misplacement rates at one college), historical rates of underplacement were higher than historical rates of overplacement for both math and English at each of the colleges, and in most cases much higher.

Implementation Findings

The seven colleges in this study all followed very similar status quo placement procedures before beginning their involvement with this project. Most of the colleges relied heavily on the results of ACCUPLACER or other single tests for placement. CAPR research teams visited each of the seven participating colleges on two separate occasions to learn what college personnel thought about both the status quo and alternative placement systems and to better understand the processes required to implement the alternative system.

While most interviewees at the colleges were quick to point out weaknesses in the status quo system, they also emphasized two strengths of that system: (1) the straightforward nature of comparing a student's score on a test with an established cut score to place students (compared with the relative opacity of using the algorithm score produced under the alternative system, which combines weighted values from a number of different sources), and (2) the related efficiency of the status quo system, which allows students to be placed into coursework very quickly, and without need to obtain additional information.

In terms of weaknesses, interviewees frequently reported their belief that the placement tests used under the status quo system were not doing a good job of placing students into the appropriate level of coursework. They also expressed strong concerns that students do not recognize how important the tests are and that some students proceed through the tests too quickly.

Overall, implementation of the multiple measures, data analytics placement system created a significant amount of up-front work to develop new processes and procedures that, once in place, generally ran smoothly and with few problems. At the beginning of the project, colleges underwent a planning process of a year or more, in close collaboration with the research team, in order to make all of the changes required to implement the alternative placement system.

Among other activities, each college did the following: (1) organized a group of people to take responsibility for developing the new system, (2) compiled a historical dataset in order to create the college's algorithms, (3) developed or improved processes for obtaining high school transcripts for incoming students and for entering transcript information into IT systems in a useful way (which in some cases was time-consuming and challenging), (4) created procedures for uploading high school data into a data system where it could be combined with test data at the appropriate time, (5) changed IT systems to capture the placement determinations derived from the use of multiple measures, (6) created new placement reports for use by students and advisors, (7) provided training to testing staff and advisors on how to interpret the new placement determinations and communicate with students about them, and (8) conducted trial runs of the new processes to troubleshoot and avoid problems during actual implementation.

While these activities were demanding, every college was successful in overcoming barriers and developing the procedures needed to support the operation of the data analytics placement system for its students. Five colleges achieved this benchmark in time for placement of students entering in the fall of 2016, while the other two colleges did so in time for new student intake in the fall of 2017.

While many interviewees believed that the alternative system would place students more fairly and accurately, they also reported challenges and concerns. These issues largely involved: (1) undertaking such an extensive reform so quickly and establishing the buy-in to do so, (2) obtaining and entering large amounts of high school transcript data into the college's computer system, (3) adjusting classroom and faculty assignments based on changed proportions of students in developmental and college-level courses, (4) not having placement information immediately available to students under the alternative system (in some cases, students had to wait a day or more to get their placement determinations), and (5) the potential limiting of access to support programs intended for underprepared (low-placing) students.

Cost Findings

We calculated costs for the five colleges participating in study intake for the fall 2016 cohort using the ingredients method (Levin, McEwan, Belfield, Bowden, & Shand, 2017). Costs are derived from the inputs used at each college, multiplied by standardized prices per input. Relative to the status quo system, new resources were required to create the algorithms, to set up and administer the collection of data used in the algorithms, and to run the alternative system at the time of placement testing. Across the five colleges, implementation of the alternative placement system added \$603,550 — or \$110 per student — to status quo fall-term costs for testing and placing students. The per-student net implementation costs ranged from \$70 to \$320 at the different colleges, with lower costs generally associated with higher numbers of students at each college. More enrollments lead to lower costs per student because the costs of creating the algorithms for the new system are mostly fixed; they do not vary with the number of students involved.

Ongoing costs in the subsequent fall term were much lower than the first-term implementation costs. Ongoing per-term costs were estimated at \$215,300 — or \$40 per student — above status quo costs. The per-student net ongoing costs ranged from \$10 to \$170 at the different colleges.

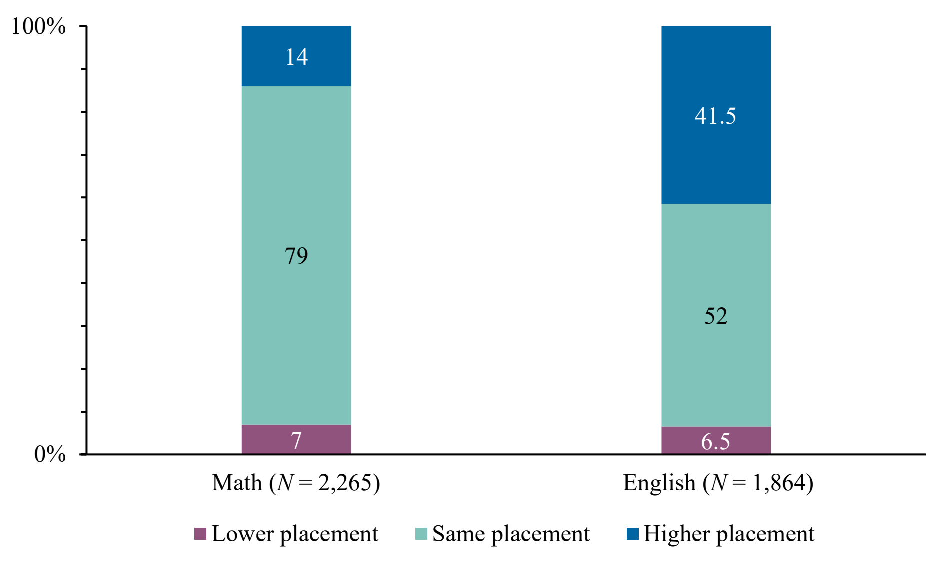
When information on the outcomes of the alternative placement system is available, cost estimates can be used as part of a cost-effectiveness analysis. Findings from such an analysis will be included in the final report.

Placement Determinations of Program Group Students

Because the multiple measures, data analytics placement system uses a different set of criteria than the status quo system, we might expect at least some changes in placement levels in math and English courses among program group students relative to what they would have been under the status quo. Importantly, however, any new placement procedure will not change the placement determinations of some students. Of the 2,455 students assigned to the program group, 92 percent took a placement test in math, and 76 percent took a placement test in English. Figure ES.1 shows how the placement determinations of such program students differed from what they would have been under the status quo. As expected, based on prior research, the proportion of higher placements outweighed the proportion of lower placements in both subject areas, particularly in English, where nearly half of program group students were placed differently than they would have been otherwise.

Figure ES.1

Observed Difference in Placement Relative to Status Quo Among Program Group Students Who Took a Placement Test in Each Subject Area



Early Impacts Findings

In this experimental study, incoming students who took a placement test were randomly assigned to be placed using either the multiple measures, data analytics system or the status quo system. This assignment method creates two groups of students — program group and control group students — who should, in expectation, be similar in all ways other than their form of placement. The overall sample for our analysis of first-term outcomes consists of 4,729 students who took a placement test at the five colleges at the time of fall 2016 entry, of whom 3,865, or about 82 percent, enrolled in at least one developmental or college-level course of any kind during the fall 2016 term. Because some students in the sample took either a math or an English placement test rather than both, the sample for our analysis of math outcomes is reduced to 4,371 students, and the sample for analysis of English outcomes is reduced to 3,533 students. We find that differences in student characteristics and in placement test scores between program and control group students are generally small and statistically insignificant, which provides reassurance that the randomized treatment procedures undertaken at the colleges were performed as intended.

Our analyses were conducted using ordinary least squares regression models in which we controlled for college fixed effects and student characteristics such as gender, race/ethnicity, age, and financial aid status as well as proxies for college preparedness.

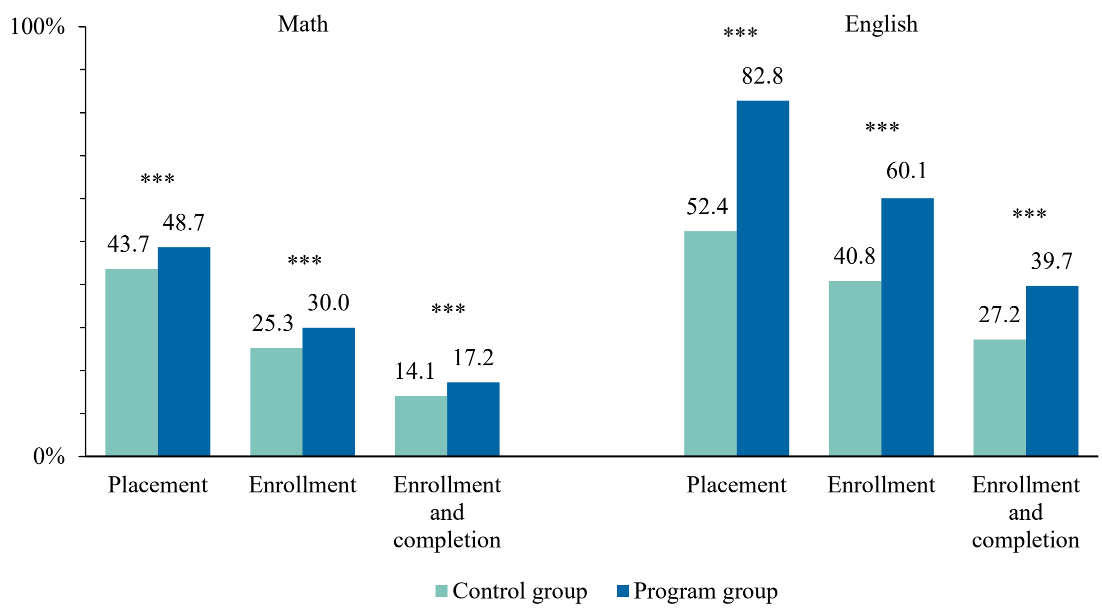
For both math and English, we consider three outcomes as shown in Figure ES.2: the rate of college-level course placement (vs. remedial course placement) in the same subject area, the rate of college-level course enrollment in the same subject area, and the rate of college-level course completion with a grade of C or higher in the same subject area.

As is shown, assignment to the program group produced positive and statistically significant effects on all three outcomes in both math and English. The impacts in English were substantially larger than the impacts in math. In math, students in the program group were, on average, 3.1 percentage points more likely to enroll in and complete (with a grade of C or higher) a college-level math course during their first term, after controlling for the full set of covariates. In English, students in the program group were 12.5 percentage points more likely to enroll in and complete a college-level English course.

We also carried out analysis on the full sample to measure the effect that assignment to the program group had on earning college-level credits in any course or courses in the first term. Students in the program group earned, on average, 0.60 more college-level credits than students in the control group ($p < .01$; control group student students earned 5.17 credits, while program group students earned 5.77 credits).

Figure ES.2

College-Level Course Outcomes in Math and English



***$p < .01$, **$p < .05$, *$p < .10$.

Finally, to examine whether program assignment led to differential first-term impacts by race/ethnicity (Black, Hispanic, White), Pell recipient status (yes, no), or gender (female, male), we conducted subgroup analyses and tested the significance of interaction effects for each subgroup. We limited these analyses to only those students who enrolled in any course at the college (because demographic information on students who did not enroll was unavailable), so the results of this analysis are not strictly causal. It is also worth noting that small sample sizes used in this first-term impacts analysis may limit the extent to which some subgroup effects are found to be statistically significant.

In math, we find that most subgroups benefitted from program group status in terms of college-level math placement, enrollment, and enrollment and completion (with a grade of C or higher) outcomes ($p < .1$); the exceptions are that we find no statistically significant treatment impacts for men across all math outcomes considered and also find no statistically significant impacts on math course completion for Black and White students.

Again in math, we find that interactions between the treatment status and each of the race/ethnicity and Pell recipient subgroups we considered are not statistically significant. This suggests that *gaps* in placement, enrollment, and completion rates in math between subgroups (other than the gender subgroups) may not have been affected by the treatment. We do find, however, that while men had higher math outcomes than women in both the control and program groups, women benefitted more from program group status in math on all three outcomes considered. For example, the male–female gap in the rate of enrollment in and completion (with a grade of C or higher) of college-level math narrowed from 4.5 percentage points among control group students to 0.4 percentage points among program group students. (The male control group rate was 19.5 percent.)

In English, we find that all subgroups benefitted from program group status on all three outcomes considered ($p < .01$). Although significance testing on interaction effects in most cases failed to reveal differential impacts by subgroup, we do find evidence of differential treatment effects by racial/ethnic subgroup on two of the three considered outcomes. White students in the control group had higher English outcomes than Black and Hispanic students in the control group, but under program group status, the racial/ethnic gaps in both the rate of placement and the rate of enrollment in college-level English narrowed or even reversed. Yet we do not find evidence that program group status narrowed the gap in the rate of completion (with a grade of C or higher) of college-level English between White and Black or between White and Hispanic students.

Looking Ahead

These early results are broadly promising, but they are based on analyses of merely one semester of data. Additional impact analyses using data that are not yet available will be performed to further evaluate the effects of using a multiple measures, data analytics system to place incoming students. The final report from this study, to be released next year, will examine a range of student outcomes for all three cohorts for a period of three to five semesters after students' initial entry into college at seven SUNY community colleges.

Chapter 1
Introduction

Placement testing has become a near-universal part of the enrollment experience for incoming community college students (Bailey, Jaggars, & Jenkins, 2015). For decades, higher education institutions of all kinds have assessed the college readiness of incoming students. Selective institutions use admissions requirements to screen students, accepting or rejecting them on the basis of test scores, high school transcripts, and other application information (Cohen, Brawer, & Kisker, 2014). Open-access institutions — which include community colleges and some four-year institutions — accept all or most students for admission but then make a determination about whether or not those students are immediately ready for college-level coursework. Students deemed not yet ready are encouraged or required to participate in remedial or developmental coursework before beginning college-level courses in those subject areas in which they are found to be academically underprepared.[1]

Colleges have traditionally used standardized placement tests to determine whether students should participate in remediation. Of community colleges surveyed by the National Assessment Governing Board in 2010, 100 percent reported using standardized tests for math placement purposes, and 94 percent reported using such tests for reading placement (Fields & Parsad, 2012). Among four-year institutions, 85 percent reported using standardized tests for math placement, and 51 percent reported using such tests for English placement (Fields & Parsad, 2012).

In recent years, however, questions have arisen about the efficacy of standardized placement tests as well as the utility of traditional developmental coursework. College practitioners and others are concerned about whether too many students are unnecessarily required to take developmental education courses before beginning college-level work. The courses require students to make a substantial investment of time and money, and many students who begin college by taking developmental coursework never complete a college credential. Indeed, research shows that the effects of traditional developmental courses are at best mixed (Bailey, 2009; Jaggars & Stacey, 2014).

Evidence also suggests that the use of placement tests alone is inadequate in determining which students need remediation (Belfield & Crosta, 2012; Scott-Clayton, 2012). Partly in response to these findings, colleges are increasingly turning to the use of

[1]Remedial courses are provided to students who are deemed not ready for college-level math or English courses or for other courses that depend on college-level reading, writing, or numeracy skills. The terms *developmental education* and *remedial education* are used interchangeably in this report.

multiple measures for assessing and placing students (Rutschow & Mayer, 2018). Multiple measures placement systems often make use of placement test results but also consider other relevant data on incoming students, such as high school grade point average (GPA). While research indicates that using multiple measures, and in particular high school GPA, may result in the improved placement of students into developmental and college-level courses (Belfield & Crosta, 2012; Scott-Clayton, 2012), there is little evidence indicating that using a multiple measures placement system influences student outcomes.

To address this gap, the Center for the Analysis of Postsecondary Research (CAPR) initiated an experimental study of multiple measures placement in partnership with the State University of New York (SUNY) and seven of its 30 community colleges: Cayuga Community College, Jefferson Community College, Niagara Community College, Onondaga Community College, Rockland Community College, Schenectady Community College, and Westchester Community College. In each setting and for each subject area, math and English, a data analytics algorithm was developed — using the college's own historical student data on a number of measures, such as placement test scores and high school GPA — to predict the likelihood of success in introductory college-level math and English courses. The alternative placement system, which incorporates the newly developed algorithm as well as cut points for placement chosen by the faculty, was then used to place incoming students into college-level or developmental courses in each subject area. Our study was designed to test whether students assessed using the alternative system (the program group) would be placed more accurately than students assessed using the status quo system (the control group) and, as a result, would be more likely to complete introductory college-level math and English courses, persist in college, and earn more college credits — key indicators of likely college credential completion.

The entire study involves three cohorts of students at the seven colleges, those who first entered the college intake process in the fall 2016, spring 2017, and fall 2017 terms.[2] Outcomes for each of these cohorts — more than 13,000 students in the full sample — will be tracked through the fall 2018 term, resulting in the collection of three to five semesters of outcomes data depending on the cohort. The final report on this study will present findings on course placement, introductory college-level course completion, credits attempted and earned, and persistence. In this interim report, we describe our overall approach to the

[2]Assignment to program and control groups in the randomized controlled trial occurred just after prospective students who began the college intake process were informed about the study, agreed to participate, and took a placement test. Some of these study participants (18 percent) did not enroll in any course at the college during the same term. For ease of exposition, we refer to all those who chose to participate in the study and took a placement test as "students." We sometimes distinguish them from "enrolled students," the somewhat smaller group of students who took a placement test and then enrolled in at least one course.

evaluation study and discuss how colleges implemented the new placement system, including how the data analytics algorithms for each college (one for math and one for English) were developed. In addition, we report on first-term impact findings for the first cohort of students (who entered the intake process at five of the seven colleges). Finally, we discuss the costs involved for these five colleges to set up and use a multiple measures placement system that employs a data analytics approach.

Our initial impact findings are promising. Among a sample of 4,729 students in the first cohort, a fifth of math program students and nearly half of English program students were placed differently than they would have been under the status quo placement system. Most of these students were placed higher than they would have been using placement tests alone. In their first semester of college, students in the math and English program groups were 3.1 and 12.5 percentage points more likely than control group students to enroll in and pass a college-level course in math or English, respectively.[3] We emphasize that these initial findings are based solely on first-term outcomes of the first cohort. The final report on this study, which will present longer term evidence on these and other outcomes for all three cohorts, will be released in 2019.

Background and Context

Developmental Education

Developmental education is a significant component of public higher education, both in terms of student enrollments and in terms of costs. Among 2003–04 beginning postsecondary students, 40 percent of those starting at public four-year institutions and 68 percent of those starting at public two-year institutions took at least one remedial course during their enrollment between 2003 and 2009 (Chen, 2016).

The primary purpose of developmental education is to equip academically underprepared students with the skills they need to succeed in college-level coursework. In addition, by restricting access to college-level courses to students who meet certain academic standards, developmental education requirements may serve the secondary purpose of protecting the academic rigor of college-level courses (Bettinger & Long, 2005).

Studies employing quasi-experimental methods have been used to isolate the causal effect of developmental education on student outcomes. The results of these studies vary. Bettinger and Long (2005), for example, used instrumental variables to study developmental

[3]The rates for control and program math group students were 14.1 percent and 17.2 percent. The rates for control and program English group students were 27.2 percent and 39.7 percent.

education in Ohio's community colleges and found that remedial education had positive effects on college persistence and bachelor's degree completion. Martorell and McFarlin (2011), on the other hand, used longitudinal data from Texas and a regression discontinuity design and found that remedial education had little to no effect on the likelihood of earning a college degree or on subsequent earnings.

Jaggars and Stacey (2014) reviewed findings from eight studies that evaluated the effectiveness of community college remedial courses across six large systems or states, all but one of which used a regression discontinuity approach. These combined studies showed that, with some exceptions, developmental education had mostly null and sometimes negative impacts on outcomes (such as persistence, passing associated college-level courses, grades in college-level courses, credits and credentials earned) for students near the placement score cutoffs. They also showed that students placed into lower levels of developmental education had a higher proportion of positive effects (five positive vs. six negative and 19 null) than students placed in developmental courses who were near the college-level cutoffs (two positive vs. 15 negative and 32 null), suggesting that developmental education may have differential effects on students depending on their level of academic preparation.

The overall body of research on the efficacy of developmental education suggests that, at best, it does not hurt students, but at worst, it may decrease the likelihood among at least some students of attaining their postsecondary education goals (Bailey et al., 2015; Bailey, Jeong, & Cho, 2010; Boatman & Long, 2010; Calcagno & Long, 2008; Crisp & Delgado, 2014; Melguizo, Bos, Ngo, Mills, & Prather, 2016; Scott-Clayton & Rodriguez, 2015). Developmental education serves to extend time in college, and long remedial sequences can consume students' financial aid as well as their own resources. These consequences can demotivate students, making them less likely to complete their programs of study (Bailey, 2009; Crisp & Delgado, 2014; Scott-Clayton & Rodriguez, 2015). In fact, only 28 percent of community college students who take a remedial course go on to earn a degree within eight years, compared with 43 percent of nonremedial students (Attewell, Lavin, Domina, & Levey, 2006).

The cost of remedial education is high; estimates of the costs to deliver remedial courses range from $1.4 billion to nearly $7 billion annually (Long & Boatman, 2013; Scott-Clayton, Crosta, & Belfield, 2014). These costs fall directly on students placed into remedial courses and indirectly on taxpayers, whose money helps subsidize public postsecondary institutions that offer remedial education. As a result, there is both a private benefit and a social benefit to ensuring that developmental education is effective, expedient, and offered to those most likely to benefit from it.

Standardized Placement Test Accuracy

Placement into remedial or college-level courses at most colleges is based on scores on a single set of standardized placement tests — most often the ACCUPLACER — in math, reading, and writing. These tests do not always assess student skills accurately, and colleges that use them may place students into developmental education courses unnecessarily (Fulton, 2012). Placement test scores are not highly correlated with success in initial college-level courses: Doing poorly on a placement test does not reliably indicate that a student would be unsuccessful in a college-level course. As a result, using test scores for placement leads to placement errors for large numbers of incoming students (Bailey et al., 2015; Belfield & Crosta, 2012; Hodara & Cox, 2016; Scott-Clayton et al., 2014).

Scott-Clayton (2012) identified large predicted "severe error rates" associated with placing students using standardized placement tests alone. A severe error rate refers to placing students in remediation who would be expected to receive a grade of B or better in college-level courses (underplacement) or placing students in college-level courses who would be expected to fail (overplacement). While both types of errors should be mitigated, Scott-Clayton's research suggests that the occurrence of underplacement far exceeds the occurrence of overplacement. Using student data from a large urban community system, she found predicted severe overplacement rates of about 6 and 5 percent in math and English but severe underplacement rates of about 18 and 29 percent in the respective subject areas. Scott-Clayton further established that these severe error rates could be reduced by employing multiple measures for placement. In particular, the high school GPA was found to be a strong predictor of success in college-level courses.

Approaches to Multiple Measures Placement

Varied measures, used alone or in combination, can be employed to place students into developmental and college-level courses. In addition to standardized placement test scores, some measures that are in current use are GPAs and other information from high school transcripts, scores on writing assessments, noncognitive tests measuring psychosocial characteristics, and student self-assessments. Varying levels of evidence support the use of each of these measures, with some more thoroughly studied than others (Barnett & Reddy, 2017).

An increasing number of colleges are exploring or beginning to use multiple measures in placement decisions. In a survey conducted in 2016, 57 and 51 percent of community colleges reported using multiple measures for placement in math and English, whereas only 27 and 19 percent reported having done so in 2011 (Rutschow & Mayer, 2018). Colleges using multiple measures have employed a variety of methods to combine particular measures in order to place students more accurately. The simplest of these is a waiver system, in which one or more criteria can be used to exempt students from developmental education requirements. Another method involves the use of decision bands; students with placement test scores within a certain range are further evaluated using measures such as high school GPA or the score on a noncognitive test to further determine placement. Alternatively, historical student performance data from a college can be analyzed to weight various measures of student assessment and achievement in a way that best predicts future outcomes, the method used in the current research. Algorithms reflecting these weights, along with chosen cut points, can then be used to place students (Barnett & Reddy, 2017).

To be useful in real-world settings, placement instruments and methods must balance accuracy with cost-efficiency. For example, scored personal essays and in-person advising meetings that leverage faculty experience can improve the accuracy of placement and increase success rates for students (Duffy, Schott, Beaver, & Park, 2014). However, undertaking these activities is much more resource-intensive than using traditional placement tests, which are largely automated and more easily scaled (Hodara, Jaggars, & Karp, 2012).

Effectiveness of Multiple Measures Placement

Studies show that multiple measures placement methods that incorporate high school information, and in particular high school GPA, can significantly improve placement at a relatively low cost (Hodara et al., 2012; Belfield & Crosta, 2012).[4] Studies by Scott-Clayton (2012) and Belfield and Crosta (2012) found that high school GPA can help predict college performance and could be used to place students more accurately than scores on placement tests alone. Both studies suggest that an optimal placement strategy would take into account both high school transcript data and placement test scores.

Results from a small randomized experiment at a Midwestern community college (Marwick, 2004) showed that students placed using either one of two multiple measures approaches were more likely to take and succeed in higher level math courses than were students placed using standardized test scores alone. One method incorporated placement test scores and performance in high school math; the other method involved an advisor-mediated student choice scenario in which test scores, high school preparation, and other factors were discussed in an advising session. While this study was very small, the results suggested that further evaluation of multiple measures placement is warranted.

Statewide changes in placement policies are allowing for broader examinations of alternative placement methods. North Carolina instituted a statewide reform that began in 2013 and was required to be used by all colleges by fall 2016. The policy exempts students

[4]Belfield and Crosta (2012) found that including additional information from the high school transcript (e.g., the number of courses taken in math or English, or the total number of high school credits) to predictive models that already included high school GPA contributed little to no additional value.

from remediation based on certain criteria. For example, students who graduated from high school within five years with a GPA of 2.6 or above are exempted from remediation. If the GPA threshold is not met, colleges also grant exemptions based on SAT or ACT scores. Only those students who do not meet the GPA or SAT/ACT requirement must take a placement test (Dadgar, Collins, & Schaefer, 2015).

In California, the 2017 passage of Assembly Bill 705 called for all community colleges in the state to modify their placement practices so that high school data is used as a primary measure of college readiness by spring 2019. While system-wide changes are underway, individual community colleges have already begun to implement multiple measures placement systems. Before passage of the bill, Long Beach City College developed an algorithm that uses student high school achievement in addition to standardized placement test scores to assess students. The algorithm weights each measure on the extent to which it predicts student performance in college courses (Long Beach City College, Office of Institutional Effectiveness, 2013). Using the multiple measures algorithm increased student placement into college-level courses from 15 to 60 percent in English and from 10 to 50 percent in math, with no significant change in student success rates (Dadgar, et al., 2015). Many other California colleges are now implementing versions of this approach, which is similar to the one undertaken in the current project.

About CAPR

Established in 2014, the Center for the Analysis of Postsecondary Readiness (CAPR) is a partnership of research scholars supported by the Institute of Education Sciences, U.S. Department of Education, and led by the Community College Research Center (CCRC) at Teachers College, Columbia University, and MDRC, a nonprofit research and development organization. In addition to the study described here, CAPR is conducting two additional major studies, one based largely on a nationally representative survey that aims to provide a comprehensive understanding of the landscape of developmental education and reform in two- and four-year colleges across the country, and one that evaluates an alternative model of developmental math programming that shortens students' time in remediation, tailors content to students' academic paths, and uses student-centered instruction. CAPR also carries out leadership and outreach activities aimed at improving college readiness.

Chapter 2

Placement System and Study Design

The current study uses a randomized controlled trial to compare the effects on student outcomes of placing students into developmental or college-level courses with either a multiple measures, data analytics placement system or a status quo system that uses just one measure, placement test scores. In order to carry out this evaluation, an alternative placement system had to be created and implemented, and random assignment procedures had to be established. Researchers and personnel at each college collaborated in these activities. We describe the approach used as well as the broader study design in this chapter.

There are five research questions guiding the study:

1. How is a multiple measures, data analytics placement system implemented, taking into account different college contexts? What conditions facilitate or hinder its implementation?

2. What effect does using this alternative placement system have on students' placements?

3. With respect to academic outcomes, what are the effects of placing students into courses using the alternative system compared with traditional procedures?

4. Do these effects vary across different subpopulations of students or by college?

5. What are the costs associated with using the alternative placement system? Is it cost-effective?

To answer Question 1, we conducted two rounds of implementation site visits to each of the seven colleges; we spoke with key personnel, including administrators, staff, and faculty. To answer Questions 2 through 4, this study tracks eligible students who first began the intake process at a participating college in the fall 2016, spring 2017, or fall 2017 term through the fall 2018 term. These students were randomly assigned to either the program group or the control group. The study design calls for impact analyses to be performed twice — once early in the study, following the end of the first cohort's first semester, and again for all three cohorts following the conclusion of the study's tracking period.

For the first set of analyses, which are presented in this report, student data were collected in early 2017 from the five colleges that began participation in the study in fall 2016, as well as from the SUNY central institutional research unit. Student outcomes data for all three cohorts will be collected from the colleges and SUNY during the spring of 2019 for the second and final set of analyses, which will allow researchers to observe students' outcomes (see Appendix Table A.1) for three to five semesters following placement, depending on the cohort.

To answer Question 5, we are carrying out a cost-effectiveness analysis that will incorporate data collected at the end of the project in spring 2019. Chapter 5 of the current report presents a cost-only analysis on the five colleges that began enrolling participating students in fall 2016. The current report also presents implementation findings (Chapter 3) and early impacts findings on the first cohort of students (Chapter 4). The final report on the results of this study will be released in 2019.

Site Descriptions

Seven SUNY colleges are participating in this study. Many had a prior interest in assessing the effectiveness of their existing placement system before they got involved, while others saw participation as an opportunity to improve knowledge and practices in student placement. The colleges are diverse in terms of size and population served (see Appendix Table A.2). While the smallest of the colleges serves roughly 5,500 students, the largest serves over 22,000 students annually. As is common in community college settings, a large portion of students at the colleges attend part-time, and many are adult learners, with between 21 and 30 percent of students over the age of 25. Most of the colleges serve large numbers of students who receive financial aid — more than 90 percent of students receive financial aid at five of the seven colleges. The colleges have transfer-out rates of between 18 and 22 percent; their three-year graduation rates are between 15 and 29 percent.

All of the colleges have an open-door admissions policy, meaning that they do not have entry requirements for incoming students beyond having graduated from high school or earned a GED. The colleges tend to serve local student populations, and most have relationships with their region's high schools both for offering dual enrollment programs and to facilitate the admissions process from high school to college. Each college has a small population of students who live on campus or who moved to attend the college.

The colleges offer a wide selection of programs of study, including a few that particular colleges have developed and gained a strong reputation for, such as nursing, electronic communications, culinary, and music programs. Further, each college has varying on-campus initiatives that reflect the goals and priorities of the college. For example, one college has made a big push to increase the diversity of its faculty to better match the student population it serves. Another college has established an academic success center and has taken part in the START-UP NY program to foster private/public partnerships. And especially germane to this study, one college has designed programs called Prep for Success and Math Boosters to help students brush up on their skills and then retest if they are not initially placed in college-level courses.

Creating a Data Analytics Placement System

Given the differences among the colleges, such as the different student populations they draw from, the data analytics algorithms employed to assess program group students were created for each college individually, using historical data on previous students at each college. The resulting algorithms and historical data also allowed us to estimate historical misplacement rates at each college (see Box 2.1). After the math and English algorithms were developed, faculty at each college chose cut points on the range of scores for each algorithm that were then used to place program group students into developmental or college-level math and English.[5]

Using Historical Data to Develop Algorithms

Historical high school and placement test data were needed to create predictive algorithms at each college. Five colleges in the study had been using ACCUPLACER tests for several years. A sixth college had been using ACCUPLACER tests for English but had transitioned from a homegrown math assessment to the ACCUPLACER set of math tests more recently; this college is therefore testing the use of the alternative placement system for English placement only in this study. The seventh college in our sample had been using COMPASS tests, standardized placement tests which were discontinued by the provider (ACT) shortly after this study began. This college is also testing the use of the alternative system for English placement only. At this college, the predictive algorithm that is being tested in the alternative placement system does not make use of any placement test scores; rather, it is based only on high school GPA and other high school data. The status quo placement system in this case uses only scores from ACCUPLACER, the test that the college selected to replace the COMPASS.

CAPR researchers worked with the appropriate personnel at each college as well as SUNY's central institutional research unit to obtain historical data on students who first enrolled during the 2011–12, 2012–13, and 2013–14 academic years. Data on multiple measures, such as high school performance and placement test scores, as well as data on outcomes in college-level courses were used to create algorithms for predicting student

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[5]The colleges often used multiple cut points on the range of each algorithm's student scores to place students into different levels of developmental coursework and different levels of college-level coursework in math and English. For this study, however, we are considering only two placement alternatives: developmental versus college-level placement.

performance in college-level math and English among students in the study sample. In some instances, data on these measures were available in college systems, stored in digital format. Other colleges maintained records of high school transcripts as digital images; in these cases, the needed data had to be entered into computer systems by hand.

In order to estimate the relationships between the measures, or "predictors," in the dataset and performance in an initial college-level course, the historical data used for analyses were restricted to students who took placement tests and enrolled in a college-level course without first having taken a developmental course. This set of students constituted our estimation sample. We then regressed success in a college-level course on various sets of predictors using a linear probability model.[6] (Alternative models are described by Hastie, Tibshirani, and Friedman [2009], but more intricate models we tested yielded similar results.)

For each of the colleges, we began by creating a model for estimating the relationship between high school GPA and success (defined as earning a grade of C or higher) in an initial college-level course in a given subject, math or English (see Equation 1 below). We then estimated the relationship between placement test scores and success in these initial college-level courses (Equation 2). A third model included both high school GPA and placement test scores for the appropriate subject (Equation 3). A fourth model added additional information where such information was available (Equation 4). Added variables include the number of years that had passed since high school completion and whether the student's diploma was a standard high school diploma or a GED, SAT scores, ACT scores, and scores on the New York State Regents Exams where they were available (see Appendix Tables A.3 and A.4), as well as interaction terms and nonlinear terms for certain variables. Identical procedures were followed for both math and English.

$$(1) \qquad \Pr(C\ or\ Better) = \alpha + (HS\ GPA)\beta_1 + \varepsilon$$

$$(2) \qquad \Pr(C\ or\ Better) = \alpha + (ACCUPLACER)\beta_1 + \varepsilon$$

$$(3) \qquad \Pr(C\ or\ Better) = \alpha + (HS\ GPA)\beta_1 + (ACCUPLACER)\beta_2 + \varepsilon$$

$$(4) \qquad \Pr(C\ or\ Better) = \alpha + (HS\ GPA)\beta_1 + (ACCUPLACER)\beta_2 + X\beta_3 + \varepsilon$$

[6]Each variable in the model was accompanied by a corresponding missing indicator. Missing indicators were entered into the model equations as 1 if a student was missing that data point and zero if the student had a value for that data point.

While researchers may look at the individual covariates in a traditional study, the focus of this analysis is the overall predictive power of each model. We therefore used the Akaike Information Criterion (AIC) to compare the models. The AIC is a measure of model fit that combines a model's log-likelihood with the number of parameters included in a model (Akaike, 1998; Burnham & Anderson, 2002; Mazerolle, 2004). When comparing models, a lower AIC statistic indicates a better fitting model (Mazerolle, 2004). The best fitting model was the one selected for use at each college in the study. Appendix Tables A.3 and A.4 list the full set of variables used in each college's algorithm for math and English.

Estimation of Historical Misplacement Rates at Each College

The data analytics algorithm that was created for each college (in each subject area) also allowed us to compute historical underplacement and overplacement rates for math and English. We define an underplaced student as one placed into a developmental course who could have succeeded in an initial college-level course in the same subject area by earning a grade of C or higher.[7] In conducting analysis on underplacement, a student's probability of succeeding in the college-level course is calculated using the parameters estimated by each college's best fitting model. We define an overplaced student as one unable to pass a college-level course who was nonetheless placed into such a course. Importantly, this is not simply the inverse of passing with a C or higher, since a D is not considered a failing grade. Nonetheless, the model for overplacement uses the same set of predictors selected in modeling underplacement. For example, if Equation 4 from above is selected as a college's best fitting model, then each student's likelihood of failing the initial college-level course is calculated using the following equation:

$$(5) \qquad \Pr(Fail) = \alpha + (HS\ GPA)\beta_1 + (ACCUPLACER)\beta_2 + X\beta_3 + \varepsilon$$

The overplacement and underplacement rates for each college are simply averages of these individual probabilities. In keeping with techniques introduced by Scott-Clayton (2012), we sum the overplacement rate and the underplacement rate to generate a total error rate.

Appendix Table A.5 shows the mean estimated underplacement, overplacement, and total error rates for each of the five colleges. The results indicate that placement accuracy is an issue in both math and English for the five colleges in this phase of the study. The

[7]Scott-Clayton (2012), Belfield and Crosta (2012), and Scott-Clayton et al. (2014) used a passing grade of B or better as the outcome of interest, arguing that this higher threshold ensures that only those who are "severely" underplaced will be identified by the model. Given our threshold of a grade of C or better, we distinguish our error rates from the rates generated in those prior studies.

proportion of misplaced students ranged from 32 to 50 percent in math and from 43 to 52 percent in English. The error rates were higher in English than in math at three colleges, and very similar to one another at one college. A fifth college had higher error rates in math than in English.

Prior research on first-time entrants in a large urban community college system (Scott-Clayton, 2012) suggests that underplacement is typically a larger problem than overplacement. Our results on historical misplacement at these five colleges are consistent with these findings. With one exception (math misplacement rates at one college), rates of underplacement were higher than rates of overplacement for both math and English at each of the colleges, and in most cases much higher.

Choosing Cut Points for Projected Placement and Pass Rates

After data analytics algorithms were established at each college, we used the coefficients from the regressions to simulate placement and success rates as a basis for faculty decisions on where to establish cut points that distinguish students ready for college-level courses from those needing remediation. Consider the following simplified example using Equation 3 from above. Let *Y* represent the predicted probability of success in a college-level course. We can use regression coefficients and a student's own placement test scores and high school GPA to predict the probability of earning a C or better in college-level math ($\hat{Y}$) for any new student *i*. A set of decision rules can then be determined based on these predicted probabilities. If the college has one level of developmental math placement and one college-level course placement, the decision rule may be:

$$Placement_{\mathrm{i}} = \begin{cases} \text{College level if } \hat{Y}_{\mathrm{i}} \geq 0.6 \\ \text{Developmental if } \hat{Y}_{\mathrm{i}} < 0.6 \end{cases}$$

For each college, we generated spreadsheets projecting the share of students that would place into a college-level course at any given cut point on *Y*, as well as the share of those students we would anticipate earning a C or better in that course. These spreadsheets were given to colleges so that faculty in the relevant departments could set cut points for students taking math or English courses.

Table 2.1 shows a hypothetical example of one such spreadsheet provided to colleges. The top panel shows projected math placement statistics, and the bottom panel shows projected placement statistics for English. The first column shows the cut point, or the minimum allowable probability of success for students, that produces the projected share of college-level placements (second column) and pass rates (conditional on college-level placement; third column). The top, highlighted row in each panel shows the historical placement and pass rates at the college.

As an example, the historical placement rate for math in the table is 30 percent. The third column shows the pass rate, based on the receipt of a grade of C or higher, in the initial (gatekeeper) college-level course. The historical pass rate for math in this example is 50 percent, conditional on placement into the college-level math course.

Table 2.1

Hypothetical Spreadsheet on Projected College-Level Placement and Completion Rates (With Grade C or Higher) at Given Cut Points

Math Success		
Cut Point (Minimum Probability of Success)	Percent Who Will Place Into College-Level Course	Percent Who Will Pass College-Level Course With Grade C or Higher
Historical	30%	50%
45%	40%	60%
55%	20%	70%
65%	10%	75%

English Success		
Cut Point (Minimum Probability of Success)	Percent Who Will Place Into College-Level Course	Percent Who Will Pass College-Level Course With Grade C or Higher
Historical	40%	60%
45%	75%	60%
55%	60%	65%
65%	20%	70%

Below each highlighted row is shown what would happen to placement and pass rates at different cut points chosen for scores on the algorithm. For math, the first cut point shown is 45 percent, which means that to be placed into college-level math under the algorithm, a student must have a predicted probability of receiving a C or higher in the gatekeeper math course of *at least* 45 percent. If this 45 percent cut point were used, Columns 2 and 3 show what share of students would be placed into college-level math under the algorithm (Column 2) and what share are projected to pass this course conditional on placement (Column 3). In this example, for math, if the 45 percent cut point were used, the algorithm would place 40 percent of students into college-level math, and 60 percent of those students would be projected to pass the course with a C or higher. The cut point differs from the projected pass rate. The cut point represents the *lowest* probability of passing for any given student; the cut point implies that every student must have that probability of passing *or higher*.[8]

Many faculty opted to create placement rules that either (1) kept pass rates in college-level courses similar to historical pass rates or (2) kept college-level placement rates similar to historical placement rates. Under the first approach, the algorithm tended to predict increases in the number of students placed into college-level coursework. For instance, in the example shown in Table 2.1, the historical pass rate for college-level English is 60 percent. A cut point of 45 percent would induce the same pass rate, 60 percent, but would place 75 percent of students into the college-level English course.

Implementing the Alternative Placement System

Colleges in the study had two options for implementing the data analytics placement system. At colleges running the system through ACCUPLACER, researchers programmed custom rules into the ACCUPLACER software for students selected to be part of the program group. The rules specified the ACCUPLACER placement determination for every combination of multiple measure values used in the algorithm, which were accessed from a pre-registration file created and uploaded with data for each incoming student.

Other colleges conducted their placement through MDRC's custom-built server and therefore did not need to create a pre-registration file. Instead, student information was sent to MDRC servers in one of two ways. Either all information was uploaded together and a placement decision was returned for each student, or students' supplemental information was uploaded in batches and test scores were uploaded individually by counselors after students completed their testing. The values of the uploaded multiple measures and test scores were then multiplied by their respective algorithm weights and summed to generate the predicted probability of success and the corresponding placement, which was returned to the college.

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[8]For instance, if the cut point were 40 percent, then every student placed into the college-level course would need to have a 40 percent chance *or greater* of passing the college-level course — most students would have above a 40 percent chance. This means we should expect the projected pass rate to be higher than the cut point. If higher cut points are used — meaning that students must have higher probabilities of passing in order to be placed into the college-level course — then the share placed into the college-level course declines but the anticipated pass rate increases because the standard for placement becomes more challenging.

Randomized Controlled Trial Procedures

The research design for this study was selected to meet What Works Clearinghouse[9] evidence standards without reservations. Our procedures were as follows. First, entering prospective first-year students arrived at each college for the intake process. Those with waivers based on SAT scores or with other exemptions from *both* math and English placement testing were not placement tested at all but rather went straight into college-level courses; they were not part of the study. Before taking placement tests, the remaining students (some of whom took tests in only one subject area, math or English[10]) were informed about the research, afforded the opportunity to seek additional information, and were able to opt out if they wished.[11] Those who continued took placement tests and were randomly assigned to be placed using either the status quo method (control group students) or the method using a multiple measures, data analytics algorithm (program group students). After taking placement tests, students were notified of their placements into developmental or college-level courses either by a college staff member or through an online portal, depending on the college. It is important to recognize that nearly one fifth of students who were randomly assigned to the control or program group and who took a placement test later decided not to enroll in any course in the fall 2016 term. We nonetheless include such persons as "students" for purposes of intention-to-treat analysis and sometimes distinguish "students" from "enrolled students," those who did enroll in at least one course at the college in the fall 2016 term.

The random assignment process was integrated into the existing placement procedures at each college, though the way that this was accomplished was tailored to individual campuses. Irrespective of the randomization mechanism, control group students followed status quo placement procedures, and program group students were placed using the alternative placement system. Students did not receive information on which group they were assigned to.

[9]Established by the Institute of Education Sciences, the What Works Clearinghouse reviews research on different programs, products, practices, and policies in education to provide educators with information needed to make evidence-based decisions.

[10]Students who took a placement test only in math were not considered in the analysis of English outcomes, and students who took a placement test only in English were not considered in the analysis of math outcomes.

[11]Students who opted out never entered our study; thus, we cannot report on the exact number of them.

Chapter 3
Implementation Findings

In addition to a randomized controlled trial conducted to measure impacts of alternative placement on student outcomes, this study includes an examination of the processes required to implement a multiple measures, data analytics placement system and considers the factors that can hinder and facilitate implementation. To carry out this examination, CAPR research teams visited each of the seven participating colleges on two separate occasions. An additional set of visits took place early — during the winter of 2015 — to provide information to college personnel about the project design and to discuss essential elements of implementation procedures; these visits were not used to collect implementation data. Subsequent visits occurred during the summer of 2016, by which point most colleges had begun enrolling students in the study. The final round of site visits took place in the spring of 2017. These visits were primarily designed to collect data about implementation, but they also served as opportunities for researchers and college personnel to discuss and troubleshoot any problems with implementation. The personnel who participated in interviews and focus groups during the two rounds of site visits included representatives from college administration, admissions, testing, advising, information technology/institutional research (IT/IR), registrars, and faculty.

Interviews and focus groups were conducted using semi-structured interview guides. With the consent of participants, these sessions were tape-recorded. Researchers took detailed notes when participants did not consent to recording. Recordings were transcribed and supplemented with researchers' notes for the purpose of analysis. Transcripts were loaded into the qualitative analysis platform Dedoose for coding and analysis. Although formal measures of inter-rater reliability were not calculated, members of the research team worked to align their applications of coding and met at regular intervals to discuss any points of uncertainty. The coding process allowed researchers to identify themes that colleges shared and ways in which colleges differed in their experiences. These results are presented below.

Status Quo Placement Procedures

The seven colleges in this study all followed very similar placement procedures before beginning their involvement with this project. Substantive differences among them were confined to the number of levels in each college's developmental math and English programs,[12] the subset of ACCUPLACER tests used for assessment, and the cut scores on

[12]In this study, we distinguish only two kinds of placements, developmental and college-level placements.

the tests chosen for placement into different courses. Under the status quo system, after students apply to each college, their files are reviewed to determine which tests, if any, they must take. Some students are exempt from placement testing; exemptions are typically based on scores on the Regents exam, AP exam, or SAT. Students who are not exempted either schedule a testing session or visit the testing center during designated drop-in hours to take placement tests. Subsequently, students meet with a counselor or advisor, who discusses the placement results and assists the students with initial course registration. In most instances, high school transcripts are not required in order to complete this process, though colleges do obtain proof of high school completion prior to a student's actual enrollment.

Strengths

During our site visits, discussions with college personnel about the status quo placement system often underscored that the system had weaknesses in placing students accurately (discussed below). However, stakeholders did note a few strengths of the system. One was the straightforward nature of comparing a student's score on a test with an established cut score. This method was easy for students, counselors, and faculty to understand, especially when compared with the relative opacity of the data analytics system used for program students in the study.

Related to the system's simplicity was its efficiency. Students could be placed into coursework very quickly, without the need to obtain additional information from a high school transcript. This was helpful when college personnel were required to process a high volume of admissions paperwork, and especially when students arrived shortly before the start of a semester. Indeed, one participating college needed to suspend study procedures for the first week of each fall semester in order to make sure that students who arrived that week could start their courses immediately rather than waiting a day for an algorithm-based placement.

Efficiency was also important in terms of the student experience. One administrator emphasized the value of having a student leave the premises with a schedule in hand after taking the placement tests. He believed that this increased the likelihood that the student would actually enroll in college in the fall, even if the course placement was not necessarily accurate.

Furthermore, many faculty were comfortable with existing tests or liked the idea of being able to rapidly learn about the ability levels of students in a given course based on a review of their test scores. A few faculty also felt that the status quo system was especially useful in placing adult learners who had been out of school for several years and whose high school records might not accurately reflect their readiness for college. For example, one told us, "Adult learners, who had been away from school for a while…. If they did well on

ACCUPLACER, it indicated to us that there was a shift in what may have been on their previous academic record."

Weaknesses

Among the most frequently expressed concerns with the status quo system was the way in which students approached the placement tests. Staff and faculty often observed that students rarely prepared for the tests. Most attributed this to students not knowing how important the tests were, a perspective that may have been reinforced by messaging from the colleges. In some cases, personnel noted that students arriving for testing were told, "We just want to see where you are to make sure we put you in the [right] courses. You're coming to [the college] no matter what. Don't even worry about this."

Others noted that students focused on getting through the tests as quickly as possible rather than taking care with their answers. Taking multiple tests in one day may have contributed to this impulse on the part of incoming students. One math faculty member told us, "I do know that we heard that in math at the time that, 'Oh, that was the third test I had to take.'" Finally, several interviewees believed that some students were not accustomed to taking tests on a computer. This concern was particularly acute in the case of older students.

The interviewees frequently reiterated their belief that the tests were not doing a good job of placing students into the appropriate level of coursework. Many college personnel felt that the tests did not properly assess student skills, and many noted that the CAPR estimates of placement errors using historical data (see Box 2.1), provided to them early in the study, confirmed their suspicions. Math and English faculty offered slightly different perspectives about this.

Math faculty often noted that the placement tests might be fine for identifying students at the top and the bottom of the distribution, but not for the middle of the distribution, which they considered to be much tougher to gauge. These faculty also voiced concerns about student mastery of different kinds of math. Some noted instances when students might place into college-level courses based on their algebra subtest score, though their arithmetic subtest score indicated a need for developmental coursework.[13]

English faculty emphasized misalignment between the skills measured by the test and the skills required to successfully complete a first-year college-level English course. Describing the ACCUPLACER sentence skills subtest, one faculty member told us:

[13]The tests are computer adaptive at each college, but not always in equivalent ways; at some colleges, students who score poorly on the arithmetic subtest do not take the algebra subtest.

> I would say the ACCUPLACER isn't a writing test. It's more like ... a multiple choice test that asks you to complete sentences. You know, "What would be the best completion of this sentence?" Because … it's not an actual writing test, some people don't test well. I would say that's also a drawback to it.

Most colleges participating in this study used the computer-graded WritePlacer, an ACCUPLACER subtest administered at some colleges, but one faculty member noted that the computer simply measured "how few errors somebody makes and how long the paragraphs … and sentences are," which did not provide an accurate portrait of a student's skills. A few colleges did have a hand-graded writing assessment, either as the primary assessment or as a method for students to appeal a placement decision. A faculty member at one of these colleges noted, however, that administering this assessment was both time- and labor-intensive.

A final concern, related by a handful of participants, involved the cost of ACCUPLACER to the college. Though some stated that the cost of each test was not that high, others noted that the aggregate cost of the ACCUPLACER contract was significant and wondered whether the college might devise an effective system that did not require this expenditure.

Implementation of the Data Analytics Placement System

Overall, implementation of the multiple measures, data analytics placement system created a significant amount of up-front work to develop new processes and procedures that, once in place, generally ran smoothly and with few problems. At the beginning of the project, colleges underwent a planning process of a year or more, in close collaboration with the research team, in order to make all of the changes required to begin implementing the alternative placement system. Each college took the following steps. (Items in italics were only required because of involvement in the research.)

- Organized a group of people to take responsibility for developing the new system and designated an overall project lead.
- Compiled a historical dataset in order to create the college's algorithms (one each for math and English) and to conduct related analyses.
- Developed or improved processes for obtaining high school transcripts for incoming students.
- Increased the number of students for whom high school data points were entered into the college computer system before students went for testing.

- Created procedures for uploading high school data into a data system where it could be combined with test data at the appropriate time.

- *Modified admissions procedures to inform students of the research and give them an opportunity to opt out.*

- *Changed testing procedures and data management systems to permit placement services to be provided to both program and control group students.*

- Changed IT systems to capture the placements derived from the use of multiple measures.

- Created new placement reports for use by students and advisors.

- Provided training to testing staff and counselors on how to interpret the new placements and communicate with students about them.

- Conducted trial runs of the new processes to troubleshoot and avoid problems during actual implementation.

- Offered opportunities for the college community to learn about the new system *and the research.*

Impact of the Alternative System on Various College Groups

The implementation experiences of different groups on campus varied, with some more directly affected by changes in the placement system than others, particularly at different stages of the process. Typically, IT staff, admissions and testing staff, registrars, and college administrators were involved intensively early on, while advising staff and faculty were more likely to be involved later.

Admissions

Implementation of the alternative placement system generally required admissions offices to become more proactive about collecting student high school transcript data because availability of the high school GPA was central to the new system. Experiences varied from college to college. Those that already required students to submit their transcripts in order to enroll were not heavily affected. Yet most of the colleges did not previously include obtaining high school transcripts as a standard part of their workflow, and tracking them down and entering associated data into college computer systems proved to be time-consuming. In some cases, college representatives had to collaborate closely with high schools to obtain transcript data more regularly and rapidly for incoming students. Collecting transcript data was particularly difficult when student applicants did not apply immediately following high school. In one case, admissions staff estimated that transcript collection and data entry doubled the office's workload.

Information Technology

In many cases, college IT departments took on the bulk of the work required to set up the alternative placement system. They needed to connect computer systems and data across different offices and interfaces, including registration files from admissions, test results from ACCUPLACER, and data on what placement determinations were made through the algorithms. In addition, IT personnel addressed problems that arose as staff in different departments began using the new procedures. Overall, IT staff reported that there was a lot of up-front work to create more automated processes that could save time later once the system was established. This up-front work took an estimated two to six weeks to accomplish. Once the system was in place and had been tested, it generally ran smoothly.

Registrars

Implementing the alternative placement system generally meant that course prerequisites had to be changed in each college's registration system. Registrars reported spending time to make sure that the new placement designations were reflected in college computer systems before registration took place for the affected semesters. With sufficient advanced notice, registrars reported that this process was manageable.

Testing

Like the admissions departments, testing staff told us that changing the placement system caused an initial increase in workload, as they had to create a new process to link testing data to other data required by the multiple measures system. Once this was done, however, the additional increase in workload was minimal. Testing staff also had to come up with new procedures for dealing with students who needed to retest and for "one-stop" students — those who go through the entire admissions and enrollment process in a single day. With regard to retesting, it was less clear whether it would benefit students to take the test again under the alternative system, given that much of their placement determination for program group students was based on their high school information. Further, the new procedures sometimes made same-day placements infeasible; instead, it often took more than a day to have all needed data to make a placement determination. This could be inconvenient for testing staff and for students.

Counseling/Advising

Staff had to gain comfort with an advising system that involved looking at placement results rather than raw test scores. This did not significantly change the workload for counseling/advising staff. However, some reported feeling torn about what to do when they were able to see both raw scores and placement results, particularly if they felt that following one or the other would benefit the student, for example, by placing them into a higher level course. Colleges fixed this problem by removing the raw scores from reports so that advisors could simply follow the placement results. After making this adjustment, most staff reported that it was easy to forget that the study was even going on as they simply followed the placement decisions on the reports.

Faculty

Overall, there was no consistently reported impact of changes on the faculty experience or approaches to instruction resulting from use of the alternative placement system. In many cases, faculty reported that nothing noticeable changed. In other cases, faculty described ways that the new placement system affected their work. A few college-level math and English instructors reported observing students with a broader range of skills and abilities in their courses, while others perceived an overall decrease in student skills and abilities. Developmental education instructors in some cases reported that their classrooms became more homogenous. In cases where faculty did notice a change in student skills and abilities, they mentioned having to adjust their instruction in order to meet the different needs of students.

Students

According to college faculty and staff, the alternative placement system did not substantially affect students' matriculation experiences, as the process for applying and enrolling generally stayed the same. Furthermore, students were not told whether they were in the program or control group. The only noticeable change to the student experience at some colleges was a delay between testing and receiving placement results. In these cases, students would have previously received their placement immediately after completing their tests. Under the alternative system, some colleges built in a one-day delay to allow time for a batch upload of data each night.

Students also no longer saw a test score, and this led to some confusion about how their placement had been determined and whether retesting was advisable. Overall, however, college personnel reported that the student experience did not change very much.

Challenges of Alternative Placement

For the most part, college representatives believed that it was important to change their placement strategies. However, they were also clear about the challenges involved in undertaking this initiative. Some of the challenges mentioned had to do with the process of engaging in reform generally, while others pertained to the multiple measures, data analytics approach to placement.

Engagement With Stakeholders

Personnel at some colleges felt that inadequate time had been spent discussing and understanding the alternative placement system. In some cases, this was because of the timeline imposed by the research, which aimed to begin student intake in the fall of 2016. In other cases, there were groups of people at the college who were not initially consulted. This may have been because they were originally viewed as less likely to be affected by changes to the placement system, or simply because of a desire to keep the process moving quickly.

> I think that's one of the key things that probably came out of all of this for all of us: to know any kind of changes that we were planning to do with placement testing in general, you'd have to be planning so much further out. You have to get these processes started so much sooner in order to really address it adequately.

College cultures varied in the way that change was perceived, and in levels of trust among groups within the college. At some colleges, there was an eagerness to try out new and promising practices. At other colleges, there appeared to be a history of mistrust of change that was perceived to be imposed by the college administration or by outside groups such as CAPR.

Use of High School Transcript Data

While some colleges had always required students to bring in high school transcripts at the time of admission, others had not. High school transcripts that were obtained were habitually scanned in pdf format and saved by all of the colleges. However, only limited numbers of colleges routinely entered data from the transcripts into the college's computer system, permitting their use in a data analytics placement system. To participate in this project, additional data entry was often needed. Yet many college leaders also acknowledged that these data were important to incorporate into the college's computer system for use in a range of analyses.

Finally, there was a certain amount of mistrust of high school GPA as an indicator of college readiness. As has been found in other settings (Hetts, 2016), interviewees had concerns about whether high school GPA was as good a predictor as a score on a standardized test such as the ACCUPLACER. For example, one interviewee commented, “Also, just one other thing is — I’m wondering if the GPAs at the various schools can be really seen as being, quote, equal.”

Changes to College Processes and Offerings

The procedural workload at the college sometimes increased, especially at the outset of the project. In most cases, considerably less work was required to sustain the alternative placement system once it was established (also see Chapter 5, Cost Analysis).

At colleges where the proportion of students in developmental and college-level courses changed considerably due to the new placement system, extra work was required to adjust classroom and faculty assignments. Department chairs reported that they had to make changes based on the different numbers of college developmental and college-level sections that were needed. In some cases, different classrooms had to be scheduled based on lower caps on the numbers of students allowed in developmental courses. At some colleges, there was a concern about whether all of the current faculty would be needed and about whether some courses, especially those in developmental reading, would continue to exist.

Changes to Testing

As noted previously, testing center staff and counselors noted that there were disadvantages to not having placement information immediately available to students under the alternative system. In some cases, the delay was viewed as a minor inconvenience. In other cases, there were concerns about making students come a second time for counseling or about missing an opportunity for testing center personnel to provide them with initial guidance on what placement results meant.

> These students were used to getting the result, and they want the results right away, and we have to tell them, “You have to wait until the next business day.” It was a lot more follow-up and phone calls to the office, instead of when you had them there.

Placement Results

There were concerns among some college staff about the impact on students of being placed too high or too low. The data analytics placement system placed some students into remedial courses even if they achieved what had been considered “college-level” scores on the placement test. College staff found it difficult to tell students that they could not take college-level courses in these situations.[14]

> The student scored above our cutoff for the math but was placed into a [remedial] math course. So I guess we were confused because I guess that we thought the purpose was to benefit the students.

In other cases, college staff worried about students being placed into college-level courses where they would struggle and possibly fail.

> I just get so concerned for those 126 people who get jumped to College Composition. I'm like, "At least give them a workshop or something," you know?

In some colleges, access to programs or majors was affected by placement determinations. For example, some student support programs explicitly targeted students in developmental courses; their enrollments could be affected by fewer students placing into these courses.

> Like I said, [TRIO] programs; it's going to destroy what we do.

In other cases, selective majors at some colleges were open only to students who were deemed college-ready. Some college personnel were concerned that students placed into developmental coursework through the alternative system would not be eligible to enter them.

> Maybe that student is trying to get into one of these high-demand majors. Now that we're saying that they have to take a remedial class, they're no longer eligible for that.

Lessons for Others

We asked college representatives about what advice they would give to colleges that were considering the use of a multiple measures, data analytics placement system. Their responses are summarized here.

Recognize that the goal of improved assessment and placement is worthwhile. Despite the difficulties that were encountered with implementation, most interviewees said that they would advise others to take on this work. Many believed that a placement system using multiple measures would be a more effective way to place students and that students would begin college in the courses that would benefit them the most.

[14]Whenever possible, placement test scores were not shown to college staff to avoid this circumstance, but there were cases where both test scores and placement results were visible.

> I think that we're going to have a lot more students in college-level courses who wouldn't have been before, and they're going to be successful.

In addition, one interviewee pointed out that the college was positively viewed in a recent accreditation process because of its participation in this project.

Be sure to have sufficient time to engage with varied groups across campus to establish buy-in. At most of the colleges, there was a sense that the project should have been rolled out more slowly and that a wider range of stakeholders should have been engaged. Most of the interviewees believed that at least some constituencies had not had enough time to understand the data analytics placement system and the implications for the college. They advised new implementers to take the time to communicate fully with different groups. One suggested an internal marketing campaign to build understanding, buy-in, and excitement about the project. Others were more focused on making sure that everyone was adequately trained in their changed roles.

> Make sure you're involving the right parties. Make sure the decision makers are sitting around the table, and make sure they understand the decisions they're making.

Anticipate possible problems that could arise, and craft solutions for them. A number of interviewees suggested that new implementers spend time coming up with varied scenarios to troubleshoot before a new placement system is launched.

> [We tried] to think of as many scenarios as possible. We realized going in that there probably would be something that would come up that we hadn't thought of. That's just human nature.

Make plans ahead of time for obtaining high school transcripts and entering the data. A suggestion was made that colleges do the necessary work with local high schools to obtain transcripts before starting a new placement system that incorporates this information. Likewise, the point was made that colleges need to plan for the data entry time required to record transcript information in a useful way.

Calculate the likely impact on course schedules, and be prepared to make necessary changes. One interviewee suggested that colleges predict how their needs for course sections are likely to change when a new placement system is in place, taking into account faculty assignments and room sizes.

> If the model looks like it's going to be placing more people at a higher level, that will have implications, and you may want to start thinking about whether you have to add more sections.… Who's going to teach those sections? And get it ready….

Reduce the burden on students as much as possible. Several personnel suggested planning ahead to make sure that services to students are not negatively affected. In particular, interviewees were concerned with minimizing the delay in providing placement information, especially during one-day student enrollment events.

Think about sustainability from the beginning. Some interviewees suggested planning beyond the short term, both to ensure that the alternative placement system has time to work and to have resources available to sustain it if it proves successful.

> I guess my advice would just be, if you decide to go to the multiple measures, let it run its course for multiple semesters before you decide to switch away from it.
>
> I've been here for a long time and know that these things come and go. I'm always willing to try something new that's going to work for the students, but we need to follow through on that and see if it was beneficial. Should it be continued? Can it be institutionalized?

Chapter 4

Early Impacts Data, Analysis, and Results

In this chapter, we discuss the analytic sample, the approach used to calculate early impacts, and the results obtained. The early impacts results for this report draw on first-term outcomes data from the first cohort of sample students, who attended five of the seven SUNY community colleges participating in this study.[15]

Data and Sample

The data used to place students and track their outcomes in this study come from two main sources: placement records and administrative data from each college. Student-level placement records include indicators for students' actual placement levels in math and English, as well as information that is needed to determine students' placements, regardless of assignment to either the program group or the control group. Placement records from each college contain high school GPAs and scores on individual ACCUPLACER tests. Additional variables included in the placement records vary by college. Examples of additional variables incorporated for certain colleges include the number of years between high school completion and college enrollment, type of diploma (high school diploma vs. GED), SAT scores, and New York State Regents Exam scores.

In addition to placement records, college administrative data were collected for any student in the study who enrolled in at least one course during the fall 2016 term. These data include demographic information, such as gender, race/ethnicity, age, and financial aid status; semesters enrolled; courses taken, including course levels; credits attempted and earned; and course grades.

We present findings from the study's first cohort of students, which includes all eligible students who went through intake at a participating college in the fall 2016 semester and opted to participate in the study. This sample excludes students who were still enrolled in high school at the time of intake, those who took their first placement test outside of the intake period for fall 2016, and those whose ACCUPLACER or writing scores on a college-

[15]The two colleges excluded from this analysis did not begin implementing the random assignment procedures until after the fall 2016 intake period.

created test placed them into an English as a second language (ESL) course.[16] Our final analytic sample for this early impacts analysis consists of 4,729 students who took a placement test at the five colleges at the time of fall 2016 entry, of whom 3,865, or about 82 percent, enrolled in at least one developmental or college-level course of any kind during the fall 2016 term.

In spring 2017, CAPR worked with the colleges and with SUNY to transfer initial data on students who had not opted out of the study and who took placement tests. For all colleges and SUNY, a list of all students enrolled in the study was provided. Institutional research personnel then delivered placement data for all students and transcript and demographic data on students who actually enrolled in any course in the fall 2016 term. This method of data extraction also allowed us to account for students who tested but who did not subsequently enroll.

Analytic Method

To test the hypothesis that a multiple measures, data analytics placement system differs from a single test placement system, we conducted an intention-to-treat analysis by comparing the average outcomes for students assigned to the program and control groups. Specifically, we estimated the following ordinary least squares regression:

$$(6) \qquad Y_i = \alpha + \beta R_i + \lambda \varphi_i + \eta X_i + \delta Z_i + \varepsilon_i$$

where Y_i represents short-term academic outcomes for student i; R_i indicates whether the individual was randomly assigned to be placed using the predictive algorithm; φ_i is an indicator for the institution a student attends; X_i is a vector of baseline covariates, including gender, race/ethnicity, age, and financial aid status; Z_i includes both math and English algorithm calculations for each student (which are essentially two indices for academic preparedness); and ε_i is a random error term. The coefficient of interest is β,[17] the effect of

[16]For colleges in which assessment and placement are managed outside of the ACCUPLACER portal (Colleges 2 and 3), we also exclude students who took their placement test over several days and/or retested in any subject. Due to a data collection error, we did not have access to complete placement information for these 45 students and therefore dropped them from our analysis. The results presented in this report are robust to the inclusion of this subgroup of students in the analytic sample.

[17]Given random assignment, ordinary least squares estimations of β ought to provide unbiased estimates of intention-to-treat effects. However, differential attrition across program and control groups could bias these estimates. Appendix Table A.6 shows test results for differential attrition across program and control groups by estimating Equation 7 without controls on an indicator for whether or not a student enrolled in any course at the college in which he or she took a placement test. There is no evidence of differential attrition from the sample.

assignment to the alternative placement system on exploratory outcomes at the end of the first (proximal) semester (see Appendix Table A.1).

Baseline Student Characteristics

Appendix Table A.7 shows baseline descriptive statistics for enrolled students in the sample, those who enrolled in any course in the fall 2016 term at one of the five colleges included in the early impacts analysis.[18] Pre-randomization characteristics for the fall 2016 enrollment cohort are reported in the first column of the table, and additional columns present results for each of the colleges separately. Fifty-two percent of enrolled students in the sample were male, and 43 percent were White. About half of all sample students enrolling in at least one course during the fall 2016 term received a federal Pell Grant for that term.

Appendix Table A.7 indicates that there is some variation in demographic characteristics across colleges. For instance, Colleges 1, 2, and 3 have a greater proportion of White enrolled sample students than do Colleges 4 and 5, which have a higher share of Hispanic enrolled sample students. Using Pell Grant receipt as a proxy for low-income status suggests that average family income for enrolled sample students also varies across colleges. While Pell Grant recipients comprise more than 60 percent of enrolled sample students from Colleges 1, 2, and 3, they represent less than half of the enrolled sample students from Colleges 4 and 5.[19]

Post-Randomization Student Characteristics

As previously discussed in Chapter 2, CAPR researchers worked with the colleges to develop college-specific data analytics algorithms, specify cut points on algorithm scores to establish decision rules for placement, and implement the resulting alternative placement system. Incoming students were randomly assigned to be placed into math and English courses using either the status quo placement system (control group) or the alternative placement system (program group). The random assignment procedure should, in expectation, ensure that students assigned to the program group are similar in all ways to those assigned into courses under the status quo placement system. Appendix Table A.8 provides evidence that participants' demographic and academic characteristics, including indicators for missing characteristics, are indeed well balanced across program and control groups for the fall 2016 study cohort. Students' individual ACCUPLACER test scores also

[18]Recall that demographic information was not obtained for students who completed a placement test but did not subsequently enroll in a course at a college during the fall 2016 term.

[19]In part, the small proportion of Pell Grant recipients in Colleges 4 and 5 can be explained by the exclusion from the final analytic sample of students who placed into ESL courses in Colleges 4 and 5, as these students are significantly more likely to be Pell recipients than their peers.

are similar across both groups.[20] Overall, the magnitude of differences between program and control groups is small and statistically insignificant, providing reassurance that randomized treatment assignment was implemented as intended.

Program Placement: Descriptive Outcomes

Because the multiple measures, data analytics placement system uses a different set of criteria than the status quo system, we might expect at least some changes in placement level in math and English[21] among program group students.[22] Importantly, however, any new placement procedure will not change the placement of some students. Figure 4.1 shows the observed changes in placement for those students in the fall 2016 cohort who took a placement test in each subject area. (For additional details, see Appendix Table A.9.)[23] Of the 2,455 students assigned to the program group, 92 percent took a placement test in math, and 76 percent took a placement test in English. Among those students who took a math placement test, 21 percent experienced a math placement different from what would have been expected under the status quo placement rules; 14 percent were placed into a higher level math course (i.e., a college-level course) than would have been expected under the status quo system, and 7 percent were placed into a lower level math course (i.e., a developmental course).[24]

Of the 76 percent who took a placement test in English, 48 percent of program group students experienced a change in their level of English placement (i.e., moved between a developmental and college-level placement); 41.5 percent placed into a higher level course, and 6.5 percent placed into a lower level course than they would have under the status quo placement system.

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[20]In order to avoid post-treatment bias, we report on and use only the student's first ACCUPLACER score received on each subject test.

[21]Students were placed into both reading and writing developmental or college-level courses using the algorithm developed for English.

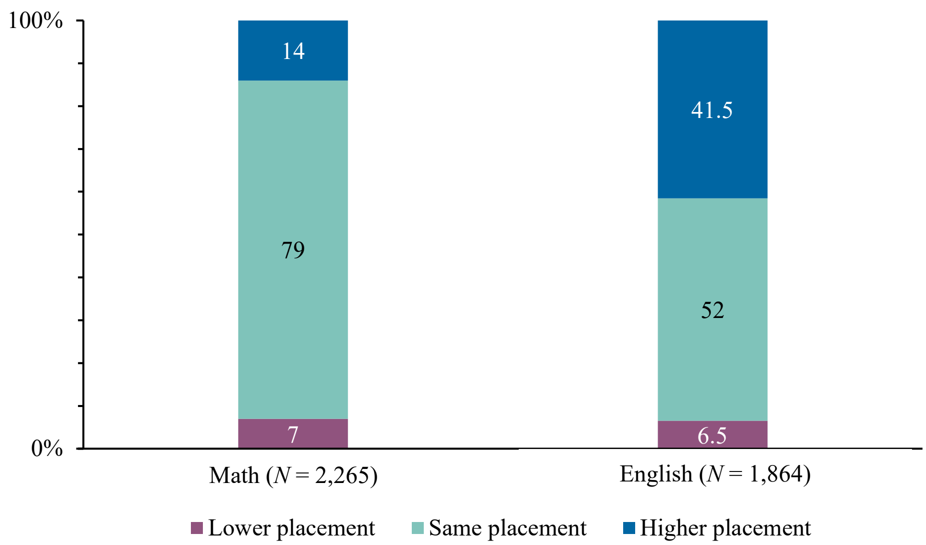
[22]A change in placement is defined as a student being placed into a developmental course rather a college-level course or vice versa. A change in the *level of either developmental or college-level course placement* is not considered a change in placement for purposes of this analysis.

[23]Unlike the intention-to-treat analysis discussed below, the descriptive calculations that yield these results do not control for any college or student characteristics.

[24]Students who were exempt from placement by test for math or English were not included in analysis for that subject area. Taking a placement test is defined as taking one or more placement subtests in a subject area.

Figure 4.1

Observed Difference in Placement Relative to Status Quo Among Program Group Students Who Took a Placement Test in Each Subject Area



In examining the data, we find that students generally entered the courses into which they were placed, if they enrolled in math or English courses at all. Compliance rates were high across math and English, ranging from 88 to 99 percent across participating colleges. Instances of noncompliance can be at least partially explained by the fact that we only consider initial placements — retesting may have changed final placements in some cases.

Treatment Effects

To test whether program assignment affected student outcomes, we constructed four estimation models that build upon each other: (1) We first calculated a simple regression, including only college fixed effects, to estimate the relationships between the treatment indicator and each outcome; (2) we then added controls for the full set of predefined demographic characteristics for gender, race/ethnicity, and age included in Appendix Table A.7; (3) we then added proxies for income, including Pell and TAP Grant[25] recipient status; and (4) we finally added the calculated math and English algorithm values for all students.

[25]The Tuition Assistance Program (TAP) is a need-based grant available to New York State residents who enroll as a first-time student at an approved postsecondary institution in the state.

Appendix Tables A.10 through A.18 show the results for each outcome of interest, including college-level placement in math and English, enrollment in college-level math and English, enrollment in and completion (with a grade of C or higher) of college-level math and English, enrollment in any college-level course, enrollment in and completion (with a grade of C or higher) of any college-level course, and college-level credits earned.[26] Importantly, because we present intention-to-treat results, students who did not enroll in any courses following placement are nonetheless included in the sample and were coded with a zero on all enrollment, completion, and credit accumulation outcomes. Because the impacts shown in the results are based on a sample of students that include those who never entered courses, they may understate the impacts on students who did in fact enroll.

Results are robust to each model specification. For the remainder of this section, we discuss results from Model 4, the preferred specification.

Math

Figure 4.2 shows the treatment effects, or the differences in outcomes between program and control group students, on college-level math placement, enrollment, and completion rates (with a grade of C or higher) in college-level math in the first term, among the 4,371 students in the first cohort who took a math placement test. For all three outcomes, there was a positive and statistically significant ($p < .01$) effect of being assigned to the program group. Students in the program group were 5.0 percentage points more likely than those in the control group to be placed in a college-level math course, 4.7 percentage points more likely to enroll in a college-level math course, and 3.1 percentage points more likely to enroll in and complete a college-level math course during their first term, after controlling for the full set of covariates.

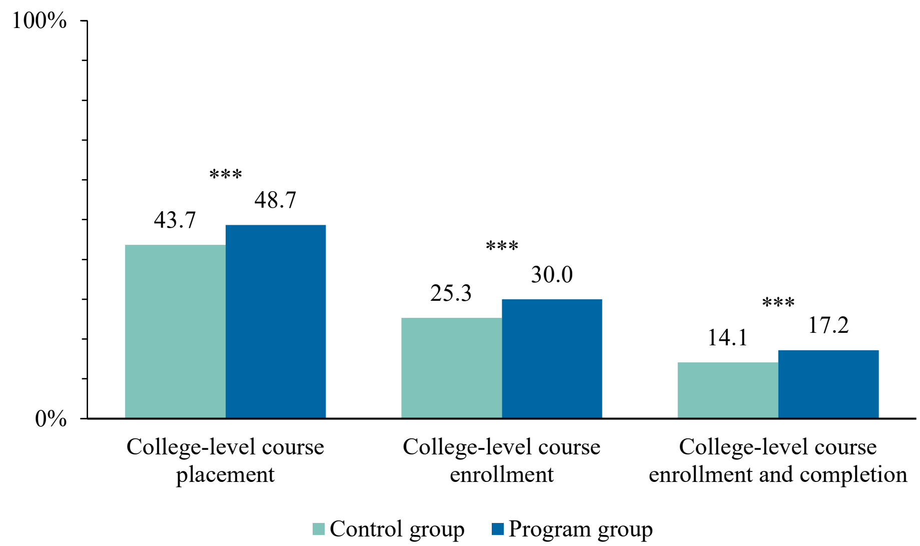
These effects may also be stated in proportional terms by dividing the percentage point differences in outcomes by the control group outcomes. Stated in this way, the treatment increased the probability of college-level math course placement by 11.4 percent, the probability of college-level math course enrollment by 18.6 percent, and the probability of college-level math course enrollment and completion by 22.0 percent. All these impact findings are statistically significant, meaning that it is highly unlikely that they are due to chance. The difference between placement and enrollment into a college-level math course

[26]Analyses presented in the current report use data from the first cohort of students' first semester and therefore can be considered an initial testing of the effects on outcomes of the alternative placement system. Academic outcomes for all three cohorts of students will be tracked for three to five semesters after random assignment, depending on when the cohort entered the study. Future analyses will evaluate each outcome at the second through fifth (distal) semesters.

can be partially explained by the fact that some students who placed into college-level math did not take a math course during their first term.[27]

Figure 4.2

Math Outcomes (Among Students Who Took a Math Placement Test)



***$p < .01$, **$p < .05$, *$p < .10$.

English

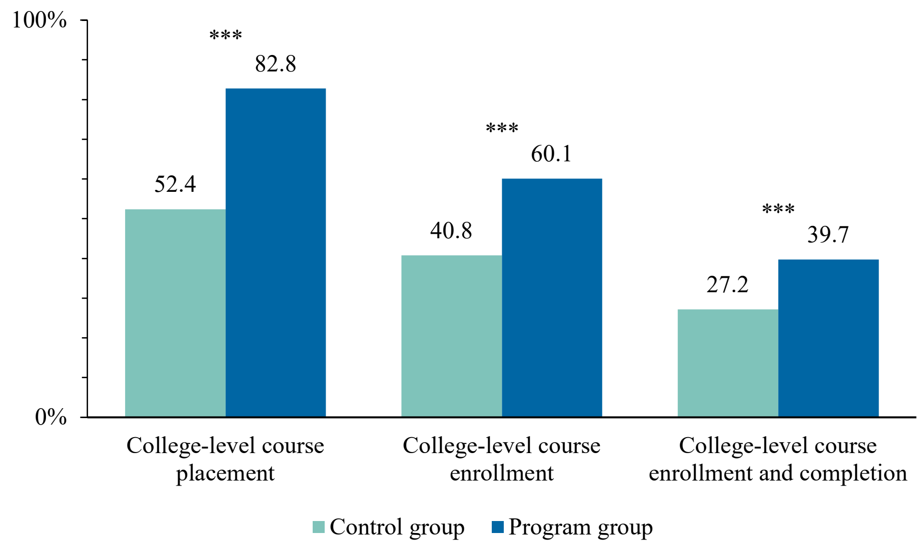
There are similarly positive, though substantially larger, statistically significant ($p < .01$) impacts for English placement, enrollment, and completion (with a grade of C or higher) among the 3,533 students in the first cohort who took an English placement test for fall 2016 entry. As shown in Figure 4.3 below, students who were in the program group were 30.4 percentage points more likely to be placed in a college-level English course, 19.3 percentage points more likely to enroll in a college-level English course, and 12.5 percentage points more likely to enroll in and complete a college-level English course in the first term. The treatment therefore increased the probability of college-level English course placement by 58.0 percent, the probability of college-level English course enrollment by 47.3 percent, and the probability of college-level English course enrollment and completion by 46.0 percent. As in the case for

[27]Among students who took a math placement test and placed into but did not enroll in a college-level math course, 31.5 percent did not enroll at any course at the college, and 65.1 percent did enroll in at least one course but did not enroll in a math course.

math, the difference between placement and enrollment into a college-level English course can be partially explained by the fact that some students who placed into college-level English did not take an English course in their first term.[28]

Figure 4.3

English Outcomes (Among Students Who Took an English Placement Test)



****p* < .01, ***p* < .05, **p* < .10.

Any College-Level Course

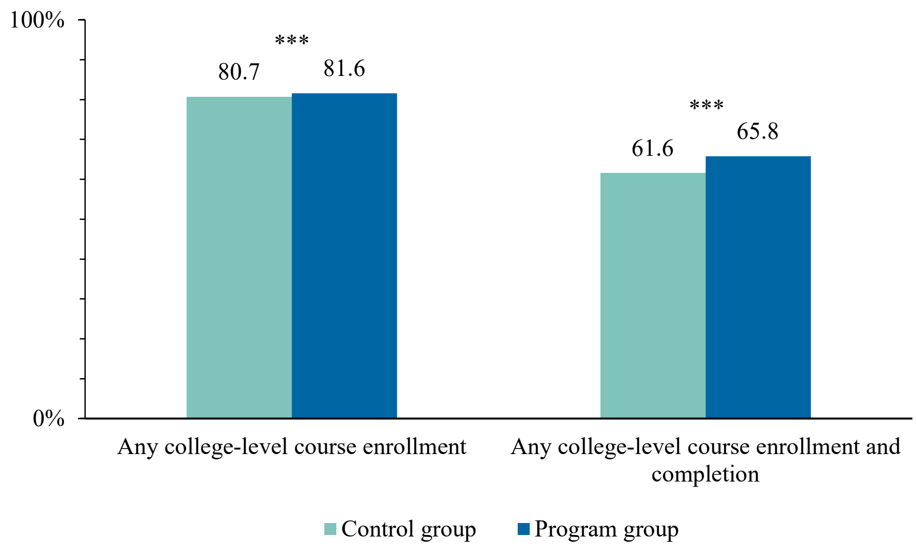
In addition to subject-specific impacts, we also test whether program or control group status had any impact on overall college-level course taking. The entire sample is used in this analysis (4,729 students). As Figure 4.4 shows, after controlling for all covariates of interest, assignment to the program group increased the probability of enrolling in any college-level course by 0.9 percentage points (or 1.1 percent) and increased the probability of enrolling and completing (with a grade of C or higher) any college-level course by 4.2 percentage points (6.8 percent). Both effects are statistically significant ($p < .01$). Despite the relatively small impacts on overall college-level course enrollment, it is important to recognize that the alternative placement system may nonetheless have placed students into college-level math

[28]Among students who took an English placement test and placed into but did not enroll in a college-level English course, 58.2 percent did not enroll at any course at the college, and 37.5 percent did enroll in at least one course but did not enroll in an English course.

and English courses who were better able to succeed in them. The greater (6.8 percent) increase in overall college-level course completion than in enrollment (1.1 percent) is consistent with this possibility.

Figure 4.4

College-Level Course Outcomes (Among All Students)



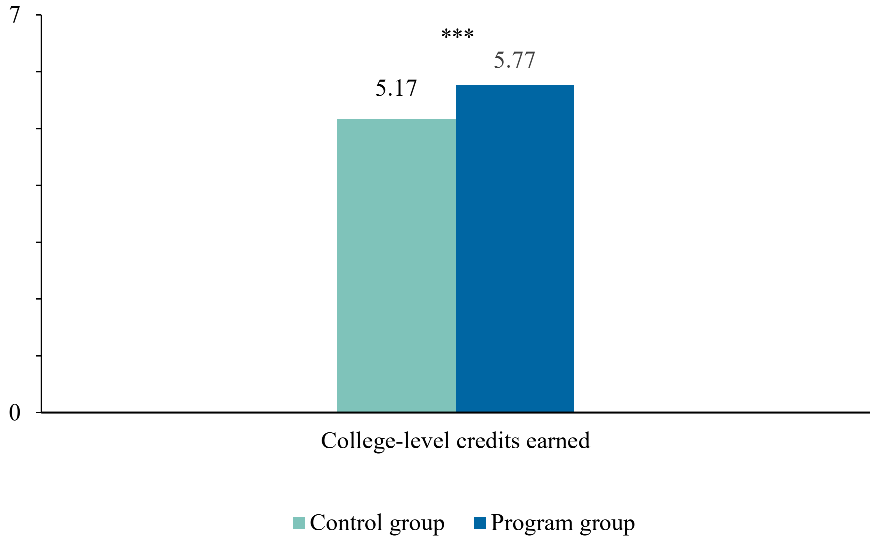
***$p < .01$, **$p < .05$, *$p < .10$.

Credit Accumulation

Finally, Figure 4.5 shows the impact that assignment to the program group had on college-level credits accumulated in the first term. Students assigned to the program group earned, on average, 0.60 more college-level credits than students in the control group ($p < .01$). This increase represents an increase of 11.6 percent in the number of college-level credits earned over the control mean of 5.17 college-level credits earned, which suggests that the multiple measures, data analytics placement system had some impact on overall college-level credits earned in the first term. This finding compares favorably with evaluation findings from other initiatives designed to increase student success in college. For example, an experimental study of summer bridge programs found that students who had participated in such programs earned an additional 0.6 credits in college after two full years (Barnett et al., 2012).

Figure 4.5

College-Level Credit Accumulation (Among All Students)



***$p < .01$, **$p < .05$, *$p < .10$.

Subgroup Analyses

To test whether program assignment led to differential treatment effects, we conduct subgroup analyses by race/ethnicity, Pell recipient status, and gender and test the significance of interaction effects between treatment status and each subgroup. The detailed results of the subgroup analyses are presented in Appendix Tables A.19 through A.36.[29] Because we are limiting this analysis to only those students who enrolled in any course at the college ("enrolled students") — a post-random assignment characteristic — these analyses are no longer causal and may produce biased estimates of treatment effects. This would be apparent if the treatment status differentially impacted enrollment patterns by subgroup. We test for this possibility (see Appendix Table A.8) by examining whether enrollment is balanced across treatment status and whether this is true for each subgroup. Post-randomization balance across subgroups conditional on college enrollment offers some assurance that there are not differential treatment impacts on college enrollment by subgroup. Nonetheless, the results described below should not be considered strictly causal. It is also worth noting that observed sample sizes may limit our power to detect statistically significant effects for

[29]Although not presented here, estimated interaction effects for each subgroup are available upon request.

smaller subgroups.[30] The larger sample sizes that will be used in the final report analyses may reveal additional differential impacts by subgroup.

Math

We find that gains in college-level math placement, enrollment, and enrollment and completion (with a grade of C or higher) were experienced by students assigned to the program group for most of the subgroups we considered ($p < .1$); the exceptions are that we find no statistically significant treatment impacts for men across all math outcomes considered and also find no statistically significant impacts on course completion for Black and White students. Importantly, small sample sizes may explain null findings for some subsamples. For example, the minimum detectable effect (MDE) given the observed precision and sample size for Black students is 8 percentage points.[31]

With the exception of the gender subgroups, interactions between the treatment status and each of the subgroups we considered are generally small and not statistically significant. This suggests that *gaps* in placement, enrollment, and completion rates in math between subgroups (other than gender subgroups) may not have been affected by the treatment. Stated another way, the statistically insignificant interactions suggest that the treatment may not have differentially impacted students by race/ethnicity or Pell Grant status.

However, unlike the other subgroups considered, women appear to have benefitted more from program group status than men across all math outcomes considered. Placement by the alternative system narrowed gender-based placement, enrollment, and enrollment and completion gaps in math at levels that are statistically significant. Use of the alternative placement system reduced the gap in college-level math placement between men and women by 7.7 percentage points (from a gap of 8.6 percentage points to a gap of 0.9 percentage points), reduced the gap in college-level math enrollment by 5.0 percentage points (from a gap of 12.2 percentage points to a gap of 7.2 percentage points), and reduced the gap in college-level math enrollment and completion by 4.5 percentage points (from a gap of 4.9 percentage points to a gap of 0.4 percentage points). Statistically significant interaction effects provide evidence that placement by the alternative system narrowed gender-based placement ($p < .01$), enrollment ($p < .1$), and enrollment and completion gaps ($p < .1$) in math. Gender and other subgroup results in math are summarized in Figures 4.6 through 4.8 below.

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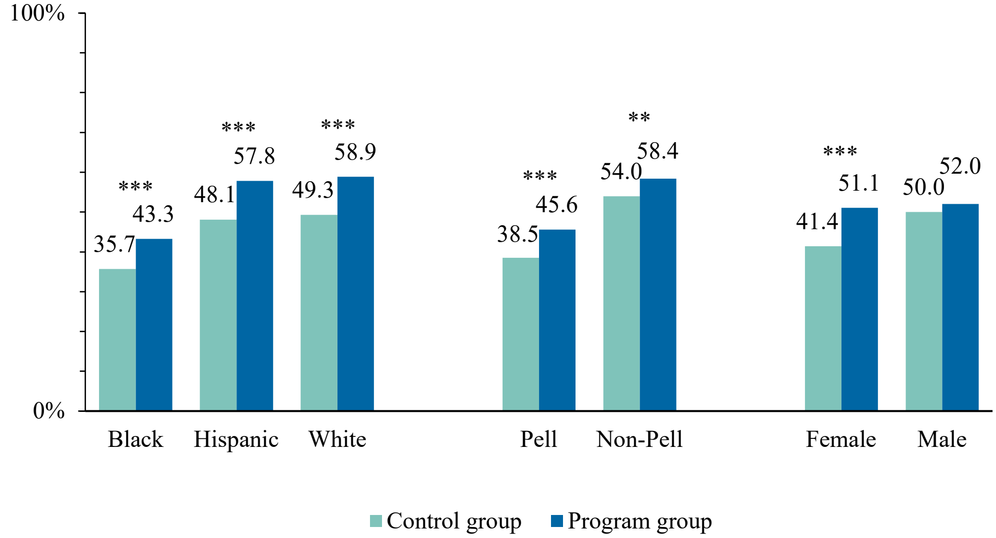
[30]Appendix Figure A.1 shows the relationship between sample size and the minimum detectable effect (MDE) based on 80 percent power, 5 percent significance, and an r^2 equal to 0.1.

[31]MDE is calculated based on 80 percent power and a 5 percent significance level for a two-tailed test.

Figure 4.6

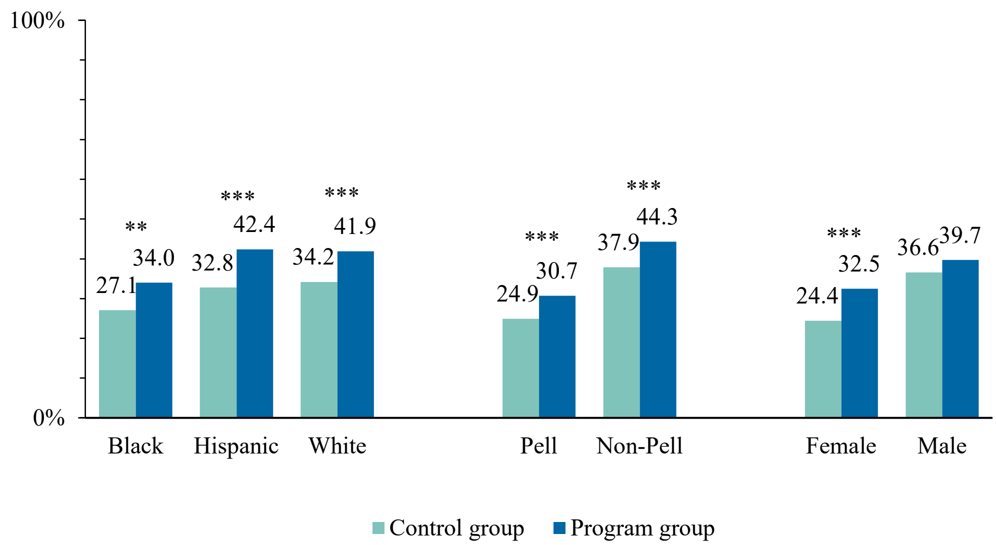
Placement in College-Level Math (Among Enrolled Students)



***$p < .01$, **$p < .05$, *$p < .10$.

Figure 4.7

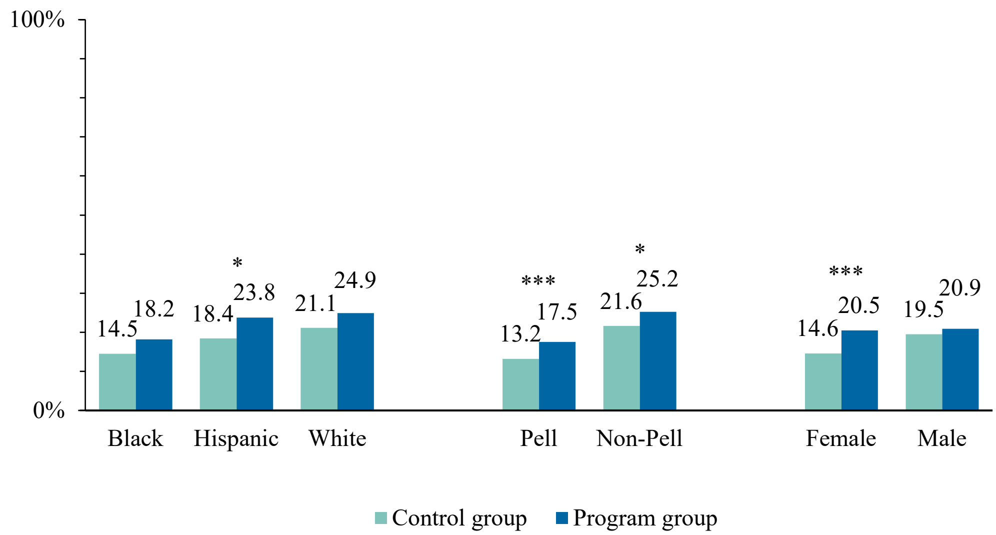
Enrollment in College-Level Math (Among Enrolled Students)



***$p < .01$, **$p < .05$, *$p < .10$.

Figure 4.8

Enrollment in and Completion of College-Level Math (Among Enrolled Students)



***$p < .01$, **$p < .05$, *$p < .10$.

English

We also conduct subgroup analyses for each of the three college-level English outcomes discussed in the main analysis. Figures 4.9 through 4.11 below summarize the results of these analyses. Overall, we find positive and statistically significant impacts on college-level English placement, enrollment, and enrollment and completion (with a grade of C or higher) for each of the subgroups we consider ($p < .01$). Although significance testing on interaction effects in many cases fails to reveal differential impacts by subgroup, statistically significant interaction effects provide suggestive evidence of larger treatment effects on college-level English placement and enrollment for Black and Hispanic students compared with White students ($p < .01$).

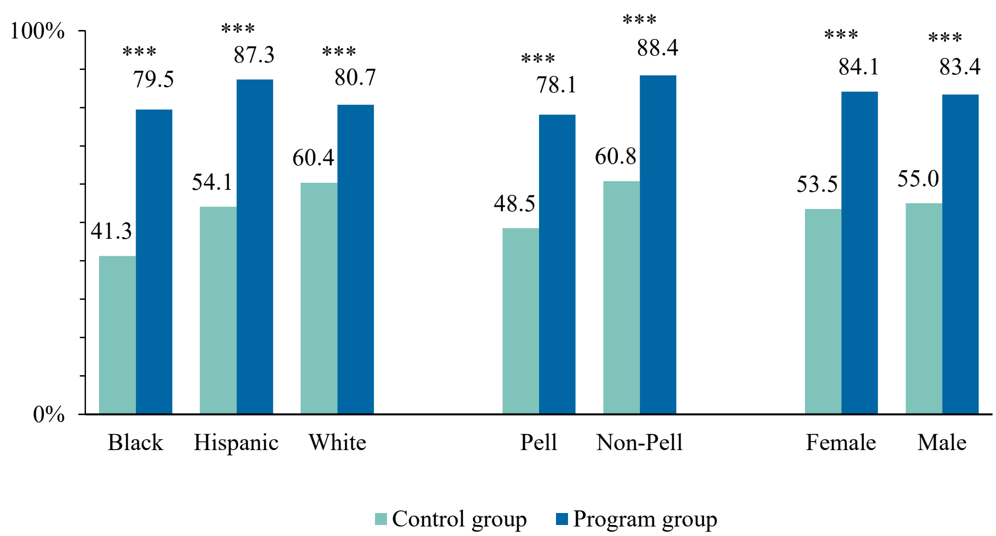
White students in the control group had higher outcomes than Black and Hispanic students in the control group, but under program group status, the racial/ethnic gaps in the placement and enrollment outcomes narrowed or even reversed. The Black–White gap in rates of placement in college-level English narrowed from 19.1 to 1.2 percentage points. (The White control group rate was 60.4 percent.) The equivalent Hispanic–White gap reversed from 1.2 percentage points in favor of White control group students to 6.6 percentage points in favor of Hispanic program group students.

The Black–White gap in rates of enrollment in college-level English reversed from 15.4 percentage points in favor of White control group students to 1.1 percentage points in favor of Black program group students. (The White control group rate was 56.3 percent.) The equivalent Hispanic–White gap reversed from 4.8 percentage points in favor of White control group students to 7.0 percentage points in favor of Hispanic control group students.

Models testing the interactions between treatment status and indicators for race/ethnicity thus suggest that placement by the alternative system may have narrowed or reversed college-level English placement and enrollment gaps in favor of racial/ethnic minorities. It is important to emphasize that we do not find evidence that the enrollment and completion gap narrowed between White and racial/ethnic minority groups.

Figure 4.9

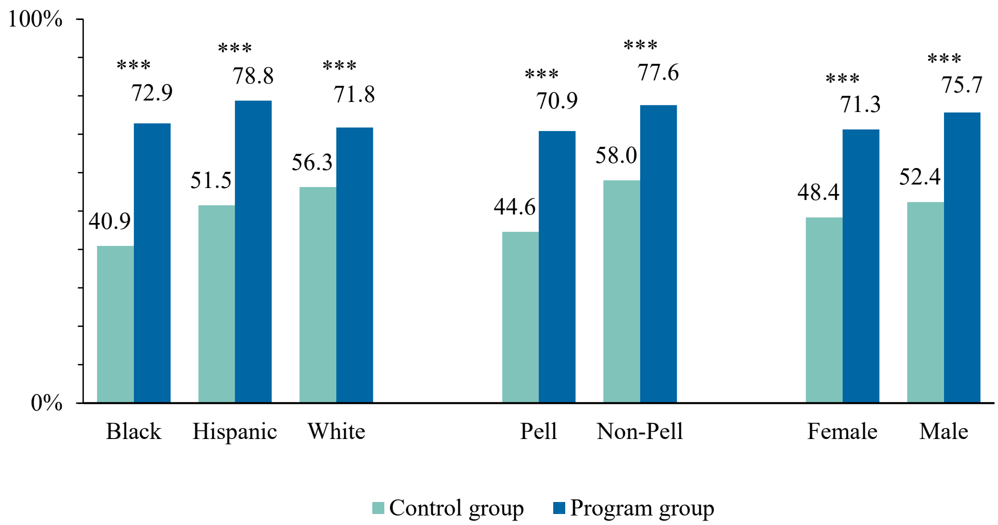
Placement in College-Level English (Among Enrolled Students)



***$p < .01$, **$p < .05$, *$p < .10$.

Figure 4.10

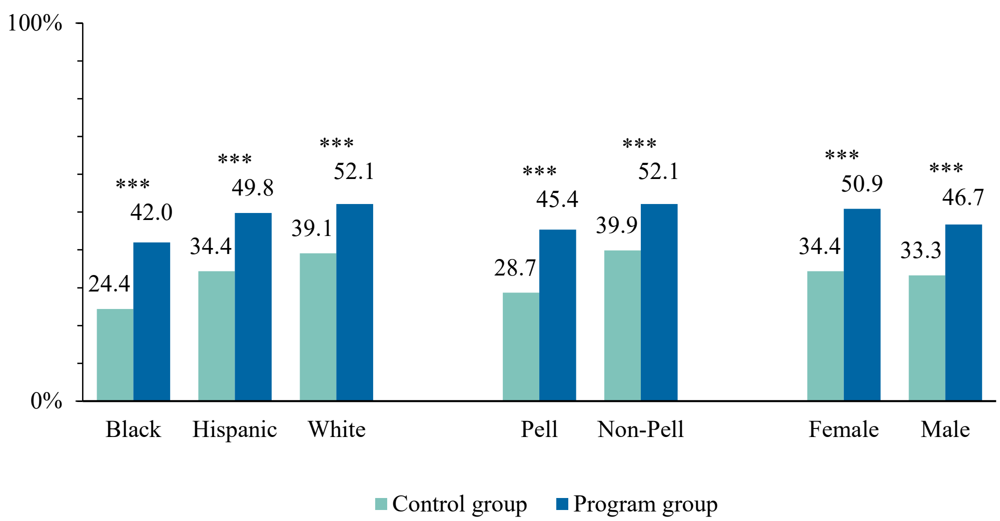
Enrollment in College-Level English (Among Enrolled Students)



***$p < .01$, **$p < .05$, *$p < .10$.

Figure 4.11

Enrollment in and Completion of College-Level English (Among Enrolled Students)



***$p < .01$, **$p < .05$, *$p < .10$.

Chapter 5
Cost Analysis

In this chapter, we provide an estimate of the first-term costs of implementing the multiple measures, data analytics placement system at the five colleges that began to invite students into the study in fall 2016, as well as an estimate of the subsequent costs of operating the system after the first year. The cost estimates of the alternative placement system are relative to the cost of the status quo testing system for placement.

First-Year Fall-Term Costs

Relative to the status quo system, there are new resource requirements for: (1) performing administrative setup and collection of data for the data analytics algorithms; (2) creating the algorithms (one each for math and English) for implementation; and (3) running the alternative placement system at the time of placement testing. For both the status quo system and the new placement system there are costs in (4) administering placement tests — although the costs per test may differ between the status quo and the new system. Also, for both options, there may be future resources required when students (5) progress into college-level courses after completing developmental coursework. If more students progress into college-level courses, colleges will have to provide extra courses. Currently, no information on differences in college-level coursework across the two options is available, so the costs of this last resource category cannot be calculated.

The costs are calculated for the five colleges using the ingredients method (Levin et al., 2017). Costs are derived from the inputs used at each college, multiplied by standardized prices per input. All costs are expressed in 2016 dollars. Information on ingredients was collected from direct interviews with personnel who implemented the new testing protocols; at three colleges, two additional sets of interviews were undertaken. Information on input prices and overhead costs were collected from secondary sources. The resulting cost estimates are the expected cost of implementing the new placement system at a college of similar size and organization as the five sample colleges.

The cost per college is given in Table 5.1. (See table notes for details.) Resources for personnel to implement the alternative placement system are divided into several groups. Within the college, there are IT/computing staff, responsible for creating new computing and data infrastructure (and for some data management); program staff, responsible for cleaning data and implementing the new placement system during and after the students take the placement tests, as well as for advising students about courses; senior staff and faculty, responsible for introducing and managing the new system; and administrative staff, responsible for supporting the implementation of the new system.

Outside the college, there is personnel time from the research team that developed the data analytics algorithms and (at some sites) applied the algorithms to determine student placement into developmental or college-level courses. These external costs are allocated evenly across the five sites. (Also, there are personnel at the SUNY system-level office who committed time to the project. Currently, these costs are not available and so are not included in estimates in Table 5.1.) In addition to personnel costs, there are also fringe benefits and all other operating costs (overhead, facilities, and materials costs). Finally, there are costs for administering the placement tests; based on their direct analysis, Rodríguez, Bowden, Belfield, and Scott-Clayton (2014) estimated these costs at \$30–44 per test.

Across the five colleges, the total cost to fully implement the new system was \$762,640 across the 5,303 students[32] in a single (fall 2016) cohort. However, this amount includes the cost of administering the placement tests, a cost that is also incurred under the status quo placement system. Therefore, the net cost of the new system is \$603,550 per cohort, or \$110 per student.

As shown in Table 5.1, the cost per student varies between \$70 and \$320. We assume that each student enters the college once, so these per-unit costs apply to each eligible student on initial intake. The variation in per-student cost is primarily driven by the number of students at each site. (Note the markedly lower numbers of students at high-cost Colleges 2 and 3 in Table 5.1.) More enrollments lead to lower costs per student because the costs of creating the algorithms for the new system are mostly fixed — that is, they do not vary with the number of students involved. Also, costs per college varied depending on how much information was previously available to determine the new placement algorithms and how many students had the requisite information. Data entry costs were lower if the college had all high school information preloaded into its databases; in contrast, data entry costs were higher if each student's information had to be entered into the computer system individually.

Interviewees did not indicate significant resource changes with respect to instruction. Potentially, the new placement system may change assignments such that more students are now in college-level courses; this would require more college-level faculty and perhaps more sections of college-level courses. However, most colleges indicated that faculty could be reassigned from teaching developmental courses to teaching college-level courses; also, few changes in class size were anticipated.

[32]Some of these students, including dual enrollment and ESL students, were excluded from the analytic sample of 4,729 students.

Subsequent-Year Fall-Term Costs

The data analytics placement system requires an initial investment to create the algorithms that are used to assess students. This investment is not necessary each semester. For ongoing operations, modest resources are required to administer the new placement system. First, resources are needed for collection of information from entering students for use in the algorithms. Second, limited additional personnel time is needed to assign students to developmental education or directly to college-level courses.

Using the same number of students as in the first semester, we estimate the costs of operating the system in the next fall term, after the algorithms have been developed. The estimates are inexact because we do not yet know what resources will be used. As shown in Table 5.2, the operating cost per student per semester over the status quo is estimated at $40. This amount is less than half of the total cost to implement the data analytics placement system in the first semester. However, this estimate is not precisely bounded: It may be as low as $10 or as high as $170.

Future Analysis on Cost-Effectiveness

The cost per student reported above is the cost of employing the data analytics system relative to the status quo system. This is called the *direct cost*. When information on the outcomes of the alternative system is available, cost estimates can be used as part of a cost-effectiveness analysis. However, for cost-effectiveness analysis, both direct and indirect costs should be included. In this case, the indirect costs are the costs of progression into college courses (Resource Category 5). These indirect costs will be calculable once there is information on how program and control group students progress through college. This analysis will be included in the final report.

Table 5.1

First-Year Fall-Term Implementation Costs for the Data Analytics Placement System

Item	Ingredient Price per FTE	College 1	College 2	College 3	College 4	College 5	Total
Personnel (FTEs)							
IT[a]	$56,230	0.18	0.10	0.18	0.05	0.30	0.80
Program[b]	$47,500	0.44	0.91	0.15	0.14	0.87	2.50
Senior/faculty[c]	$62,500	0.16	0.07	0.25	0.25	0.25	0.98
Administrative support[d]	$35,950	0.05	0.05	0.05	0.05	0.05	0.25
Evaluator time[e]	$56,230	0.10	0.10	0.10	0.10	0.10	0.50
Total personnel costs		$48,600	$60,160	$40,180	$32,470	$81,000	$262,410
Fringe benefits[f]		$16,040	$19,850	$13,260	$10,720	$26,730	$86,600
Overheads/facilities[g]		$47,140	$58,360	$38,970	$31,500	$78,570	$254,540
Placement test administration[h]		$10,770	$12,930	$21,540	$31,260	$82,590	$159,090
Total cost		$122,550	$151,300	$113,950	$105,950	$268,890	$762,640
Total cost over status quo		$111,780	$138,370	$92,410	$74,690	$186,300	$603,550
Students per semester		359	431	718	1,042	2,753	5,303
Average cost over status quo		$310	$320	$130	$70	$70	$110

SOURCE: Ingredients information on FTEs from interviews with key personnel at five colleges.

NOTES: 2016 dollars. Present values (d = 3%). Rounded to $10.
[a]Salary data from https://www.cs.ny.gov/businesssuite/Compensation/Salary-Schedules/index.cfm?nu=PST&effdt=04/01/2015&archive=1&fullScreen
[b]Annual salary (Step 4, Grade 13) from https://www.suny.edu/media/suny/content-assets/documents/hr/UUP_2011-2017_ProfessionalSalarySchedule.pdf
[c]Midpoint MP-IV from https://www.suny.edu/hr/compensation/salary/mc-salary-schedule/
[d]https://www.cs.ny.gov/businesssuite/Compensation/Salary-Schedules/index.cfm?nu=CSA&effdt=04/01/2015&archive=1&fullScreen
[e]Estimated from timesheets by CAPR researchers.
[f]Uprated from ratio of fringe benefits to total salaries (Integrated Postsecondary Education Data System [IPEDS] data, 2013, 846 public community colleges).
[g]Uprated from ratio of all other expenses to total salaries (IPEDS data, 2013, 846 public community colleges).
[h]Cost to administer placement test from Rodríguez et al. (2014).

Table 5.2

Subsequent-Year Fall-Term Operating Costs for the Data Analytics Placement System

Item	Ingredient Price per FTE	College 1	College 2	College 3	College 4	College 5	Total
Personnel (FTEs)							
IT[a]	$56,230	0.02	0.01	0.02	0.01	0.03	0.08
Program[b]	$47,500	0.44	0.91	0.15	0.14	0.87	2.50
Senior/faculty[c]	$62,500	0.02	0.01	0.03	0.03	0.03	0.10
Administration[d]	$35,950	0.01	0.01	0.01	0.01	0.01	0.03
Total personnel costs		$23,150	$44,140	$10,020	$8,640	$44,520	$130,470
Fringe benefits[e]		$7,640	$14,570	$3,310	$2,850	$14,690	$43,060
Overheads/facilities[f]		$7,410	$14,130	$3,210	$2,760	$14,250	$41,770
Placement test administration[g]		$10,770	$12,930	$21,540	$31,260	$82,590	$159,090
Total operating cost (TOC)[h]		$48,970	$85,770	$38,080	$45,510	$156,050	$374,390
TOC over status quo		$38,200	$72,840	$16,540	$14,250	$73,460	$215,300
Students per semester		359	431	718	1,042	2,753	5,303
Average operating cost over status quo		$110	$170	$20	$10	$30	$40

SOURCE: Ingredients information on FTEs from interviews with key personnel at five colleges.

NOTES: 2016 dollars. Present values (d = 3%). Rounded to $10.
[a]Salary data from https://www.cs.ny.gov/businesssuite/Compensation/Salary-Schedules/index.cfm?nu=PST&effdt=04/01/2015&archive=1&fullScreen
[b]Annual salary (step 4, grade 13) from https://www.suny.edu/media/suny/content-assets/documents/hr/UUP_2011-2017_ProfessionalSalarySchedule.pdf
[c]Midpoint MP-IV from https://www.suny.edu/hr/compensation/salary/mc-salary-schedule/
[d]https://www.cs.ny.gov/businesssuite/Compensation/Salary-Schedules/index.cfm?nu=CSA&effdt=04/01/2015&archive=1&fullScreen
[e]Uprated from ratio of fringe benefits to total salaries (IPEDS data, 2013, 846 public community colleges).
[f]Uprated from ratio of all other expenses to total salaries (IPEDS data, 2013, 846 public community colleges).
[g]Cost to administer placement test from Rodríguez et al. (2014).
[h]Operating cost refers to running of new placement system after initial algorithm has been developed and tested.

Chapter 6

Conclusion

This report is the first of two that will emerge from this random assignment study of a multiple measures, data analytics placement system used at seven SUNY community colleges for students who entered in the fall 2016, spring 2017, and fall 2017 terms. In this report, we describe how this alternative placement system — which uses high school transcript data and other information, in addition to placement test scores — was designed and developed, how it was implemented, how the use of the system affected the college community, and its cost. We also report on the first-semester impacts of the alternative placement system on the first cohort of 4,729 students who took a placement test at five of the seven colleges for fall 2016 entry. In the final report, to be published in 2019, we will report on the impact of the placement system on the full analytic sample of students — about 13,000 persons who entered the seven colleges in all three cohorts.

Most of our implementation findings are based on interviews with college personnel at all seven colleges. We found that the design and implementation of the alternative placement system was considerably more complex than initially expected by both the research team and participating staff at the colleges. Colleges often set up formal or informal committees to manage the work of developing and setting up the system; most also had a designated project lead. Steps needed to create the alternative system and get it to run smoothly took substantial time to accomplish. These included understanding how the new system would work; establishing buy-in from multiple stakeholders; developing the data analytics algorithms; deciding on cut points for placement; and creating procedures for newly required tasks such as data entry of high school transcript data, building and testing the technical infrastructure for alternative placement, and adjusting course offerings to match changes in placement.

While these activities were demanding, every college was successful in overcoming barriers and developing the procedures needed to support the operation of the data analytics placement system for its students. Five colleges achieved this benchmark in time for placement of students entering in the fall of 2016, while the other two colleges did so in time for new student intake in the fall of 2017. Our results concerning implementation suggest that establishing a data analytics placement system is challenging but manageable. They also suggest that some colleges that want to implement a similar system may need technical assistance both to conduct analyses using historical student data that are necessary to create data analytics algorithms for math and English and to integrate these algorithms and other required placement components into the existing college placement computer infrastructure.

In our cost analysis, we estimate that implementing the alternative placement system added between $74,690 and $186,300 per college in first-year fall-term costs (an average of $110 per student) to the status quo costs for testing and placing students. Ongoing (subsequent-year fall-term) costs were much lower, ranging from $14,250 to $73,460 per college (an average of $40 per student) over status quo costs. In the final report we will have sufficient data to provide a cost-effectiveness analysis.

Our early impacts findings are restricted to first-term impacts among the first cohort of students. While only exploratory, they suggest that the multiple measures, data analytics placement system used at the participating institutions holds considerable promise. Across the five colleges included in the analysis, a greater proportion of students in the first cohort who were placed using the data analytics system (those in the program group) were assigned to college-level courses in their first term than of those placed using the status quo placement system (those in the control group). In addition, a greater proportion of program group students enrolled in and passed (with a grade of C or higher) college-level courses in math and English.

Our first-term subgroup analyses are not strictly causal and involve smaller sample sizes than our full sample analyses. Initial findings suggest that women benefitted more than men from program group status in math on all outcomes considered, and that Black and Hispanic students benefitted more than White students from program group status in English for placement and enrollment but not for completion (with a grade of C or higher).

Key findings are summarized as follows:

- Twenty-one percent of program group math students and 48 percent of program group English students were placed differently than they would have been under the status quo system.

- Most of those program group students who were placed differently were placed higher than they would have been under the status quo system (i.e., were placed in college-level rather than developmental coursework). Among math students, 14 percent placed higher, while 7 percent placed lower. Among English students, 41.5 percent placed higher, while 6.5 percent placed lower.

- Program group students were 3.1 and 12.5 percentage points more likely than control group students to enroll in and complete (with a grade of C or higher) a college-level math or English course in the first semester. (The enrollment and completion rates among the control group were 14.1 percent in math and 27.2 percent in English.)

- Program group students earned 0.6 more college credits in the first semester than did students in the control group (5.77 vs. 5.17 credits).

- While men had higher math outcomes than women in both the control and program groups, women benefitted more from program group status in math on all three outcomes considered. For example, the male–female gap in the rate of enrollment in and completion (with a grade of C or higher) of college-level math narrowed from 4.5 percentage points among control group students to 0.4 percentage points among program group students. (The male control group rate was 19.5 percent.)

- White students in the control group had higher English outcomes than Black and Hispanic students in the control group, but under program group status, the racial/ethnic gaps in both the rate of placement and the rate of enrollment in college-level English narrowed or even reversed. Yet we do not find evidence that program group status narrowed the gap in the rate of completion (with a grade of C or higher) of college-level English between White and Black or White and Hispanic students.

These early results are broadly positive but assess outcomes based on merely one semester of data. Further impact analyses using additional data will be performed to evaluate the effects of using a multiple measures, data analytics system to place incoming students rather than a system based on scores on standardized placement tests alone. The final report on this study will examine a range of outcomes three to five semesters after students' initial entry into college at seven SUNY community colleges. Our final sample of over 13,000 students in a randomized controlled trial covering this time period will allow us to present impact findings in which we can have greater confidence than those provided here. Most important, we will be able to estimate over a greater time period student progress on our two most central (confirmatory) outcomes: completion of introductory college-level math and English courses and accumulation of college credits. We will also gain a better understanding of whether results differ by college and by student subgroup.

Appendix A

Supplementary Tables and Figures

Appendix Table A.1

Student Academic Outcome and Process Measures Used in the Evaluation

Outcome/Process Measure	Description of Measure	Proximal (Semester 1)	Distal (Semesters 2–5)
Initial placement level changed	Binary indicator that placement changed	Exploratory	Exploratory
Initial placement level	Categorical indicator of placement level	Exploratory	Exploratory
Subject area courses attempted	Binary indicators of courses attempted (e.g., college-level, dev ed. 1, dev ed. 2, etc.)	Exploratory	Exploratory
Subject area courses completed	Binary indicators of courses completed (e.g., college-level, dev ed. 1, dev ed. 2, etc.)	Exploratory	Exploratory
Subject area sequence completed	**Completed introductory college-level (gatekeeper) course**	Exploratory	**Confirmatory**
Credits attempted	Number of college-level credits attempted	Exploratory	Exploratory
Credits earned	**Number of college-level credits earned**	Exploratory	**Confirmatory**
Completion	Earned a degree or certificate	Exploratory	Exploratory
Persistence	Enrollment status in each subsequent semester	Exploratory	Exploratory

Appendix Table A.2

College Characteristics[a]

	Institution						
Characteristic	Cayuga	Jefferson	Niagara	Onondaga	Rockland	Schenectady	Westchester
General college information							
Student population	7,001	5,513	7,712	23,984	10,098	8,458	22,093
Full-time faculty	69	80	151	194	122	79	215
Part-time faculty	170	177	0	480	409	0	2
Student/faculty ratio	20	18	16	23	23	23	16
% receiving financial aid	92	91	92	92	56	92	70
Demographics							
Race/ethnicity (%)							
American Indian or Alaska Native	0	1	1	1	0	1	1
Asian	1	2	1	3	5	7	4
Black or African American	5	7	11	12	18	14	21
Hispanic/Latino	3	11	3	5	20	6	32
Native Hawaiian or other	0	0	0	0	0	1	0
White	85	73	80	49	39	67	33
More than one race/ ethnicity	2	3	2	3	2	2	2
Race/ethnicity unknown	3	3	1	27	15	2	5
Nonresident alien	1	1	0	0	1	0	1
Gender (%)							
Female	60	58	59	52	54	53	53
Male	40	42	41	48	46	47	47
Age (%)							
Under 18	30	17	19	24	10	37	1
18–24	44	52	60	55	63	40	69
25–65	26	31	21	21	26	23	30
Unknown	0	0	0	0	0	0	0
Retention/graduation rates (%)							
Full-time students	56	55	63	57	68	56	64
Part-time students	28	30	47	34	56	50	53
Three-year graduation rate	24	27	28	20	29	20	15
Transfer-out rate	18	19	18	22	19	22	18

[a]Based on fall 2015 IPEDS data.

Appendix Table A.3

Math Algorithm Components by College

College	High School GPA	Years Since High School Graduation	HS Diploma/ GED Status	Regents Math Score	SAT Math Score	ACCUPLACER Arithmetic Score	ACCUPLACER Algebra Score	ACCUPLACER College-Level Math
College 1	X	X	X			X	X	X
College 2	X	X	X	X	X	X	X	X
College 3	X	X	X			X	X	
College 4	X	X				X	X	X
College 5	X	X	X				X	

Appendix Table A.4

English Algorithm Components by College

College	High School GPA	Years Since High School Graduation	HS Diploma/ GED Status	ACCUPLACER Reading Score	ACCUPLACER Sentence Skills Score	WritePlacer or Other Writing Score[a]
College 1	X	X	X	X	X	
College 2	X	X	X	X	X	X
College 3	X	X	X	X		X
College 4	X	X		X	X	X
College 5	X	X	X	X		

[a]To test writing skills, some colleges administered WritePlacer, an ACCUPLACER subtest, while others administered a test created by the college.

Appendix Table A.5

Historical Underplacement, Overplacement, and Total Error Rates[a]

Subject Area	Error Rates (%)	College 1	College 2	College 3	College 4	College 5
	Overplaced	24.0	5.7	12.3	11.2	15.8
Math	Underplaced	8.3	44.7	29.1	36.0	18.5
	Total error rate	32.3	50.4	41.3	47.1	34.3
	Overplaced	12.0	15.2	13.7	8.4	10.7
English	Underplaced	30.7	29.8	33.7	43.7	40.4
	Total error rate	42.7	45.0	47.5	52.1	51.1

[a]Computed using student data from 2011–2014.

Appendix Table A.6

Effect of Program Assignment on College Enrollment

Treatment Status and Model Indicators	(1)
Program assignment	-0.008 (0.011)
Control mean	0.821
College fixed effects	YES
Demographic indicators	NO
Income indicators	NO
College preparedness measures	NO
Observations	4,729

NOTES: Robust standard error in parentheses.
***$p < .01$, **$p < .05$, *$p < .10$.

Appendix Table A.7

Baseline Descriptive Student Characteristics by College (Among Enrolled Students)

	Overall		College 1		College 2		College 3		College 4		College 5	
Characteristic	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Female (%)	48	50	58	49	48	50	52	50	50	50	44	50
Race/ethnicity (%)												
White	43	49	83	38	78	42	74	44	38	49	31	46
American Indian/Native Alaskan	1	8	1	10	2	13	4	19	0	6	0	7
Asian	3	18	0	6	2	14	0	0	6	25	3	17
Black	18	39	7	26	17	38	21	41	22	42	18	38
Hispanic	22	41	7	25	0	0	1	9	30	46	25	43
Pacific Islander	0	2	0	0	1	8	0	0	0	0	0	0
More than one race/ethnicity	11	32	1	12	0	0	0	0	3	17	19	39
Nonresident alien	0	3	1	9	0	0	0	0	0	3	0	0
Race/ethnicity unknown	2	15	0	0	0	0	0	0	0	0	4	20
Race/ethnicity missing	12	33	0	0	12	33	76	43	5	22	0	0
Age at entry	19.94	5.57	20.10	6.77	22.06	7.70	21.03	6.15	20.43	5.89	18.99	4.25
Age at entry missing (%)	0	0	0	0	0	0	0	0	0	0	0	0
Pell Grant recipient (%)	49	50	64	48	66	47	61	49	36	48	47	50
Pell Grant status missing (%)	5	22	0	0	0	0	37	48	0	0	0	0
Total	3,865		327		408		673		1,002		2,319	

Appendix Table A.8

Post-Randomization Characteristics by Treatment Assignment

Characteristic	Control Mean	Program Mean	Treatment-Diff	*p*-value	Observations
Female	47.50%	47.90%	0.40%	0.76	3,865
Gender missing	17.80%	18.70%	0.90%	0.43	4,729
Race/ethnicity					
White	43.50%	41.70%	-1.80%	0.30	3,382
American Indian/Native Alaskan	0.70%	0.70%	0.00%	0.81	3,382
Asian	3.10%	3.70%	0.60%	0.34	3,382
Black	16.90%	19.20%	2.30%	0.09	3,382
Hispanic	21.90%	21.50%	-0.40%	0.77	3,382
Pacific Islander	0.10%	0.10%	0.00%	0.96	3,382
More than one race/ethnicity	11.50%	10.90%	-0.60%	0.57	3,382
Nonresident alien	0.10%	0.10%	0.00%	0.61	3,382
Race/ethnicity unknown	2.30%	2.10%	-0.20%	0.76	3,382
Race/ethnicity missing	28.30%	28.70%	0.40%	0.76	4,729
Age at entry	19.9	20	0.10	0.52	3,593
Age at entry missing	17.80%	18.70%	0.90%	0.43	4,729
Pell Grant recipient	50.10%	53.30%	3.20%	0.06	3,672
Missing Pell Grant info	4.40%	3.70%	-0.70%	0.23	4,729
TAP Grant recipient	39.10%	39.60%	0.50%	0.78	3,721
Missing TAP Grant info	3.40%	3.40%	0.00%	0.99	4,729
GED recipient	4.50%	4.20%	-0.30%	0.57	4,600
Missing GED status	2.90%	2.70%	-0.20%	0.79	4,729
High school GPA (100 scale)	78	78	0.00%	0.97	1,862
High school GPA (missing)	59.80%	61.70%	1.90%	0.18	4,729
ACCUPLACER subtest scores					
Arithmetic	45	45.9	0.90	0.26	3,439
Algebra	53.1	53.7	0.60	0.77	4,407
College-level math	35.5	35.4	-0.10	0.89	455
Reading	72.3	71.9	-0.40	0.47	3,696
Sentence skills	76.3	76.1	-0.20	0.12	1,072
Writing	6.1	6.1	0.00	0.11	3,324
Total	2,274	2,455			4,729

Appendix Table A.9

Differences in Placement Relative to Status Quo for Program Group Students

Sample and Measure	(1) Exempt From Placement Test in Subject Area	(2) Took Placement Test	(3) Same Placement	(4) Placement Changed	(5) Higher Placement	(6) Lower Placement
Math Placement						
N	190	2,265	1,795	470	310	160
Percent of total program group sample	7.74	92.26	73.12	19.14	12.63	6.52
Percent of students placed in math	-	100.00	79.25	20.75	13.69	7.06
English Placement						
N	591	1,864	967	897	774	123
Percent of total program group sample	24.07	75.93	39.39	36.54	31.53	5.01
Percent of students placed in English	-	100	51.88	48.12	41.52	6.60

Appendix Table A.10

Effect of Program Assignment on Placement in College-Level Math

Treatment Status and Model Indicators	(1)	(2)	(3)	(4)
Program assignment	0.044***	0.047***	0.049***	0.050***
	(0.014)	(0.014)	(0.014)	(0.014)
Control mean	0.437			
College fixed effects	YES	YES	YES	YES
Demographic indicators	NO	YES	YES	YES
Income indicators	NO	NO	YES	YES
College preparedness measures	NO	NO	NO	YES
Observations	4,371	4,371	4,371	4,371

NOTES: Robust standard errors shown in parentheses. The model from Column 1 includes only fixed effects for college and no additional controls. Column 2 includes fixed effects for colleges and controls for demographic indicators including race/ethnicity, gender, and age. Column 3 includes college fixed effects, controls for demographic indicators and proxies for income including Pell and TAP Grant recipient status. Column 4 includes all the previous controls plus calculated math and English algorithm values, which serve as proxies for college preparedness.

***$p < .01$, **$p < .05$, *$p < .10$.

Appendix Table A.11

Effect of Program Assignment on Enrollment in College-Level Math

Treatment Status and Model Indicators	(1)	(2)	(3)	(4)
Program assignment	0.040***	0.045***	0.047***	0.047***
	(0.013)	(0.012)	(0.012)	(0.012)
Control mean	0.253			
College fixed effects	YES	YES	YES	YES
Demographic indicators	NO	YES	YES	YES
Income indicators	NO	NO	YES	YES
College preparedness measures	NO	NO	NO	YES
Observations	4,371	4,371	4,371	4,371

NOTES: Robust standard errors shown in parentheses. The model from Column 1 includes only fixed effects for college and no additional controls. Column 2 includes fixed effects for colleges and controls for demographic indicators including race/ethnicity, gender, and age. Column 3 includes college fixed effects, controls for demographic indicators and proxies for income including Pell and TAP Grant recipient status. Column 4 includes all the previous controls plus calculated math and English algorithm values, which serve as proxies for college preparedness.

***$p < .01$, **$p < .05$, *$p < .10$.

Appendix Table A.12

Effect of Program Assignment on Enrollment in and Completion of College-Level Math

Treatment Status and Model Indicators	(1)	(2)	(3)	(4)
Program assignment	0.028**	0.030***	0.031***	0.031***
	(0.011)	(0.010)	(0.010)	(0.010)
Control mean	0.141			
College fixed effects	YES	YES	YES	YES
Demographic indicators	NO	YES	YES	YES
Income indicators	NO	NO	YES	YES
College preparedness measures	NO	NO	NO	YES
Observations	4,371	4,371	4,371	4,371

NOTES: Robust standard errors shown in parentheses. Completion is defined as earning a grade of C or better. The model from Column 1 includes only fixed effects for college and no additional controls. Column 2 includes fixed effects for colleges and controls for demographic indicators including race/ethnicity, gender, and age. Column 3 includes college fixed effects, controls for demographic indicators and proxies for income including Pell and TAP Grant recipient status. Column 4 includes all the previous controls plus calculated math and English algorithm values, which serve as proxies for college preparedness.

***$p < .01$, **$p < .05$, *$p < .10$.

Appendix Table A.13

Effect of Program Assignment on Placement in College-Level English

Treatment Status and Model Indicators	(1)	(2)	(3)	(4)
Program assignment	0.298***	0.301***	0.302***	0.304***
	(0.015)	(0.015)	(0.014)	(0.014)
Control mean	0.524			
College fixed effects	YES	YES	YES	YES
Demographic indicators	NO	YES	YES	YES
Income indicators	NO	NO	YES	YES
College preparedness measures	NO	NO	NO	YES
Observations	3,533	3,533	3,533	3,533

NOTES: Robust standard errors shown in parentheses. The model from Column 1 includes only fixed effects for college and no additional controls. Column 2 includes fixed effects for colleges and controls for demographic indicators including race/ethnicity, gender, and age. Column 3 includes college fixed effects, controls for demographic indicators and proxies for income including Pell and TAP Grant recipient status. Column 4 includes all the previous controls plus calculated math and English algorithm values, which serve as proxies for college preparedness.

***$p < .01$, **$p < .05$, *$p < .10$.

Appendix Table A.14

Effect of Program Assignment on Enrollment in College-Level English

Treatment Status and Model Indicators	(1)	(2)	(3)	(4)
Program assignment	0.183***	0.192***	0.193***	0.193***
	(0.016)	(0.014)	(0.014)	(0.014)
Control mean	0.408			
College fixed effects	YES	YES	YES	YES
Demographic indicators	NO	YES	YES	YES
Income indicators	NO	NO	YES	YES
College preparedness measures	NO	NO	NO	YES
Observations	3,533	3,533	3,533	3,533

NOTES: Robust standard errors shown in parentheses. The model from Column 1 includes only fixed effects for college and no additional controls. Column 2 includes fixed effects for colleges and controls for demographic indicators including race/ethnicity, gender, and age. Column 3 includes college fixed effects, controls for demographic indicators and proxies for income including Pell and TAP Grant recipient status. Column 4 includes all the previous controls plus calculated math and English algorithm values, which serve as proxies for college preparedness.

***p < .01, **p < .05, *p < .10.

Appendix Table A.15

Effect of Program Assignment on Enrollment in and Completion of College-Level English

Treatment Status and Model Indicators	(1)	(2)	(3)	(4)
Program assignment	0.118***	0.124***	0.125***	0.125***
	(0.016)	(0.014)	(0.014)	(0.014)
Control mean	0.272			
College fixed effects	YES	YES	YES	YES
Demographic indicators	NO	YES	YES	YES
Income indicators	NO	NO	YES	YES
College preparedness measures	NO	NO	NO	YES
Observations	3,533	3,533	3,533	3,533

NOTES: Robust standard errors shown in parentheses. Completion is defined as earning a grade of C or better. The model from Column 1 includes only fixed effects for college and no additional controls. Column 2 includes fixed effects for colleges and controls for demographic indicators including race/ethnicity, gender, and age. Column 3 includes college fixed effects, controls for demographic indicators and proxies for income including Pell and TAP Grant recipient status. Column 4 includes all the previous controls plus calculated math and English algorithm values, which serve as proxies for college preparedness.

***p < .01, **p < .05, *p < .10.

Appendix Table A.16

Effect of Program Assignment on Enrollment in Any College-Level Course

Treatment Status and Model Indicators	(1)	(2)	(3)	(4)
Program assignment	0.001	0.009***	0.009***	0.009***
	(0.011)	(0.003)	(0.003)	(0.003)
Control mean	0.807			
College fixed effects	YES	YES	YES	YES
Demographic indicators	NO	YES	YES	YES
Income indicators	NO	NO	YES	YES
College preparedness measures	NO	NO	NO	YES
Observations	4,729	4,729	4,729	4,729

NOTES: Robust standard errors shown in parentheses. The model from Column 1 includes only fixed effects for college and no additional controls. Column 2 includes fixed effects for colleges and controls for demographic indicators including race/ethnicity, gender, and age. Column 3 includes college fixed effects, controls for demographic indicators and proxies for income including Pell and TAP Grant recipient status. Column 4 includes all the previous controls plus calculated math and English algorithm values, which serve as proxies for college preparedness.

***$p < .01$, **$p < .05$, *$p < .10$.

Appendix Table A.17

Effect of Program Assignment on Enrollment in and Completion of Any College-Level Course

Treatment Status and Model Indicators	(1)	(2)	(3)	(4)
Program assignment	0.034**	0.041***	0.042***	0.042***
	(0.014)	(0.011)	(0.011)	(0.011)
Control mean	0.616			
College fixed effects	YES	YES	YES	YES
Demographic indicators	NO	YES	YES	YES
Income indicators	NO	NO	YES	YES
College preparedness measures	NO	NO	NO	YES
Observations	4,729	4,729	4,729	4,729

NOTES: Robust standard errors shown in parentheses. Completion is defined as earning a grade of C or better. The model from Column 1 includes only fixed effects for college and no additional controls. Column 2 includes fixed effects for colleges and controls for demographic indicators including race/ethnicity, gender, and age. Column 3 includes college fixed effects, controls for demographic indicators and proxies for income including Pell and TAP Grant recipient status. Column 4 includes all the previous controls plus calculated math and English algorithm values, which serve as proxies for college preparedness.

***$p < .01$, **$p < .05$, *$p < .10$.

Appendix Table A.18

Effect of Program Assignment on College-Level Credits Earned

Treatment Status and Model Indicators	(1)	(2)	(3)	(4)
Program assignment	0.503***	0.572***	0.593***	0.599***
	(0.150)	(0.130)	(0.129)	(0.129)
Control mean	5.170			
College fixed effects	YES	YES	YES	YES
Demographic indicators	NO	YES	YES	YES
Income indicators	NO	NO	YES	YES
College preparedness measures	NO	NO	NO	YES
Observations	4,729	4,729	4,729	4,729

NOTES: Robust standard errors shown in parentheses. The model from Column 1 includes only fixed effects for college and no additional controls. Column 2 includes fixed effects for colleges and controls for demographic indicators including race/ethnicity, gender, and age. Column 3 includes college fixed effects, controls for demographic indicators and proxies for income including Pell and TAP Grant recipient status. Column 4 includes all the previous controls plus calculated math and English algorithm values, which serve as proxies for college preparedness.

***$p < .01$, **$p < .05$, *$p < .10$.

Appendix Table A.19

Effect of Program Assignment on Placement in College-Level Math by Race/Ethnicity

Treatment Status and Model Indicators	(1)	(2)	(3)	(4)
Black students only				
Program assignment	0.078**	0.079**	0.085**	0.076**
	(0.039)	(0.038)	(0.038)	(0.032)
Control mean	0.357			
Observations	571	571	571	571
Hispanic students only				
Program assignment	0.082**	0.092**	0.092**	0.097***
	(0.037)	(0.037)	(0.037)	(0.028)
Control mean	0.481			
Observations	696	696	696	696
White students only				
Program assignment	0.093***	0.094***	0.095***	0.096***
	(0.025)	(0.025)	(0.025)	(0.025)
Control mean	0.493			
Observations	1,301	1,301	1,301	1,301
College fixed effects	YES	YES	YES	YES
Demographic indicators	NO	YES	YES	YES
Income indicators	NO	NO	YES	YES
College preparedness measures	NO	NO	NO	YES

NOTES: Robust standard errors shown in parentheses. The model from Column 1 includes only fixed effects for college and no additional controls. Column 2 includes fixed effects for colleges and controls for demographic indicators including race/ethnicity, gender, and age. Column 3 includes college fixed effects, controls for demographic indicators and proxies for income including Pell and TAP Grant recipient status. Column 4 includes all the previous controls plus calculated math and English algorithm values, which serve as proxies for college preparedness.

***p < .01, **p < .05, *p < .10.

Appendix Table A.20

Effect of Program Assignment on Placement in College-Level Math by Pell Recipient Status

Treatment Status and Model Indicators	(1)	(2)	(3)	(4)
Pell recipients only				
Program assignment	0.067***	0.070***	0.071***	0.071***
	(0.022)	(0.022)	(0.022)	(0.022)
Control mean	0.385			
Observations	1,763	1,763	1,763	1,763
Non-Pell recipients only				
Program assignment	0.050**	0.048**	0.048**	0.044**
	(0.023)	(0.023)	(0.023)	(0.018)
Control mean	0.540			
Observations	1,633	1,633	1,633	1,633
College fixed effects	YES	YES	YES	YES
Demographic indicators	NO	YES	YES	YES
Income indicators	NO	NO	YES	YES
College preparedness measures	NO	NO	NO	YES

NOTES: Robust standard errors shown in parentheses. The model from Column 1 includes only fixed effects for college and no additional controls. Column 2 includes fixed effects for colleges and controls for demographic indicators including race/ethnicity, gender, and age. Column 3 includes college fixed effects, controls for demographic indicators and proxies for income including Pell and TAP Grant recipient status. Column 4 includes all the previous controls plus calculated math and English algorithm values, which serve as proxies for college preparedness.

***$p < .01$, **$p < .05$, *$p < .10$.

Appendix Table A.21

Effect of Program Assignment on Placement in College-Level Math by Gender

Treatment Status and Model Indicators	(1)	(2)	(3)	(4)
Female students only				
Program assignment	0.101***	0.103***	0.105***	0.097***
	(0.023)	(0.023)	(0.023)	(0.019)
Control mean	0.414			
Observations	1,701	1,701	1,701	1,262
Male students only				
Program assignment	0.016	0.016	0.020	0.020
	(0.022)	(0.022)	(0.022)	(0.021)
Control mean	0.500			
Observations	1,862	1,862	1,862	1,862
College fixed effects	YES	YES	YES	YES
Demographic indicators	NO	YES	YES	YES
Income indicators	NO	NO	YES	YES
College preparedness measures	NO	NO	NO	YES

NOTES: Robust standard errors shown in parentheses. The model from Column 1 includes only fixed effects for college and no additional controls. Column 2 includes fixed effects for colleges and controls for demographic indicators including race/ethnicity, gender, and age. Column 3 includes college fixed effects, controls for demographic indicators and proxies for income including Pell and TAP Grant recipient status. Column 4 includes all the previous controls plus calculated math and English algorithm values, which serve as proxies for college preparedness.

***$p < .01$, **$p < .05$, *$p < .10$.

Appendix Table A.22

Effect of Program Assignment on Enrollment in College-Level Math by Race/Ethnicity

Treatment Status and Model Indicators	(1)	(2)	(3)	(4)
Black students only				
Program assignment	0.069*	0.070*	0.076**	0.069**
	(0.037)	(0.036)	(0.036)	(0.032)
Control mean	0.271			
Observations	571	571	571	571
Hispanic students only				
Program assignment	0.080**	0.091**	0.092***	0.096***
	(0.036)	(0.035)	(0.035)	(0.031)
Control mean	0.328			
Observations	696	696	696	696
White students only				
Program assignment	0.074***	0.076***	0.077***	0.077***
	(0.026)	(0.026)	(0.026)	(0.026)
Control mean	0.342			
Observations	1,301	1,301	1,301	1,301
College fixed effects	YES	YES	YES	YES
Demographic indicators	NO	YES	YES	YES
Income indicators	NO	NO	YES	YES
College preparedness measures	NO	NO	NO	YES

NOTES: Robust standard errors shown in parentheses. The model from Column 1 includes only fixed effects for college and no additional controls. Column 2 includes fixed effects for colleges and controls for demographic indicators including race/ethnicity, gender, and age. Column 3 includes college fixed effects, controls for demographic indicators and proxies for income including Pell and TAP Grant recipient status. Column 4 includes all the previous controls plus calculated math and English algorithm values, which serve as proxies for college preparedness.

***$p < .01$, **$p < .05$, *$p < .10$.

Appendix Table A.23

Effect of Program Assignment on Enrollment in College-Level Math by Pell Recipient Status

Treatment Status and Model Indicators	(1)	(2)	(3)	(4)
Pell recipients only				
Program assignment	0.056***	0.058***	0.057***	0.058***
	(0.021)	(0.021)	(0.020)	(0.020)
Control mean	0.249			
Observations	1,763	1,763	1,763	1,763
Non-Pell recipients only				
Program assignment	0.066***	0.067***	0.067***	0.064***
	(0.024)	(0.023)	(0.024)	(0.021)
Control mean	0.379			
Observations	1,633	1,633	1,633	1,633
College fixed effects	YES	YES	YES	YES
Demographic indicators	NO	YES	YES	YES
Income indicators	NO	NO	YES	YES
College preparedness measures	NO	NO	NO	YES

NOTES: Robust standard errors shown in parentheses. The model from Column 1 includes only fixed effects for college and no additional controls. Column 2 includes fixed effects for colleges and controls for demographic indicators including race/ethnicity, gender, and age. Column 3 includes college fixed effects, controls for demographic indicators and proxies for income including Pell and TAP Grant recipient status. Column 4 includes all the previous controls plus calculated math and English algorithm values, which serve as proxies for college preparedness.

***$p < .01$, **$p < .05$, *$p < .10$.

Appendix Table A.24

Effect of Program Assignment on Enrollment in College-Level Math by Gender

Treatment Status and Model Indicators	(1)	(2)	(3)	(4)
Female students only				
Program assignment	0.085***	0.083***	0.086***	0.081***
	(0.021)	(0.021)	(0.021)	(0.020)
Control mean	0.244			
Observations	1,701	1,701	1,701	1,701
Male students only				
Program assignment	0.025	0.029	0.031	0.031
	(0.022)	(0.022)	(0.022)	(0.022)
Control mean	0.366			
Observations	1,862	1,862	1,862	1,862
College fixed effects	YES	YES	YES	YES
Demographic indicators	NO	YES	YES	YES
Income indicators	NO	NO	YES	YES
College preparedness measures	NO	NO	NO	YES

NOTES: Robust standard errors shown in parentheses. The model from Column 1 includes only fixed effects for college and no additional controls. Column 2 includes fixed effects for colleges and controls for demographic indicators including race/ethnicity, gender, and age. Column 3 includes college fixed effects, controls for demographic indicators and proxies for income including Pell and TAP Grant recipient status. Column 4 includes all the previous controls plus calculated math and English algorithm values, which serve as proxies for college preparedness.

***$p < .01$, **$p < .05$, *$p < .10$.

Appendix Table A.25

Effect of Program Assignment on Enrollment in and Completion of College-Level Math by Race/Ethnicity

Treatment Status and Model Indicators	(1)	(2)	(3)	(4)
Black students only				
Program assignment	0.039	0.039	0.042	0.037
	(0.030)	(0.030)	(0.030)	(0.028)
Control mean	0.145			
Observations	571	571	571	571
Hispanic students only				
Program assignment	0.047	0.053*	0.051*	0.054*
	(0.031)	(0.030)	(0.030)	(0.028)
Control mean	0.184			
Observations	696	696	696	696
White students only				
Program assignment	0.037	0.037	0.037	0.038
	(0.023)	(0.023)	(0.023)	(0.023)
Control mean	0.211			
Observations	1,301	1,301	1,301	1,301
College fixed effects	YES	YES	YES	YES
Demographic indicators	NO	YES	YES	YES
Income indicators	NO	NO	YES	YES
College preparedness measures	NO	NO	NO	YES

NOTES: Robust standard errors shown in parentheses. Completion is defined as earning a grade of C or better. The model from Column 1 includes only fixed effects for college and no additional controls. Column 2 includes fixed effects for colleges and controls for demographic indicators including race/ethnicity, gender, and age. Column 3 includes college fixed effects, controls for demographic indicators and proxies for income including Pell and TAP Grant recipient status. Column 4 includes all the previous controls plus calculated math and English algorithm values, which serve as proxies for college preparedness.

***$p < .01$, **$p < .05$, *$p < .10$.

Appendix Table A.26

Effect of Program Assignment on Enrollment in and Completion of College-Level Math by Pell Recipient Status

Treatment Status and Model Indicators	(1)	(2)	(3)	(4)
Pell recipients only				
Program assignment	0.043**	0.043***	0.043***	0.043***
	(0.017)	(0.017)	(0.017)	(0.017)
Control mean	0.132			
Observations	1,763	1,763	1,763	1,763
Non-Pell recipients only				
Program assignment	0.039*	0.038*	0.038*	0.036*
	(0.021)	(0.021)	(0.021)	(0.019)
Control mean	0.216			
Observations	1,633	1,633	1,633	1,633
College fixed effects	YES	YES	YES	YES
Demographic indicators	NO	YES	YES	YES
Income indicators	NO	NO	YES	YES
College preparedness measures	NO	NO	NO	YES

NOTES: Robust standard errors shown in parentheses. Completion is defined as earning a grade of C or better. The model from Column 1 includes only fixed effects for college and no additional controls. Column 2 includes fixed effects for colleges and controls for demographic indicators including race/ethnicity, gender, and age. Column 3 includes college fixed effects, controls for demographic indicators and proxies for income including Pell and TAP Grant recipient status. Column 4 includes all the previous controls plus calculated math and English algorithm values, which serve as proxies for college preparedness.

***$p < .01$, **$p < .05$, *$p < .10$.

Appendix Table A.27

Effect of Program Assignment on Enrollment in and Completion of College-Level Math by Gender

Treatment Status and Model Indicators	(1)	(2)	(3)	(4)
<u>Female students only</u>				
Program assignment	0.064***	0.062***	0.063***	0.059***
	(0.018)	(0.018)	(0.018)	(0.017)
Control mean	0.146			
Observations	1,701	1,701	1,701	1,701
<u>Male students only</u>				
Program assignment	0.012	0.013	0.014	0.014
	(0.018)	(0.018)	(0.018)	(0.018)
Control mean	0.195			
Observations	1,862	1,862	1,862	1,862
College fixed effects	YES	YES	YES	YES
Demographic indicators	NO	YES	YES	YES
Income indicators	NO	NO	YES	YES
College preparedness measures	NO	NO	NO	YES

NOTES: Robust standard errors shown in parentheses. Completion is defined as earning a grade of C or better. The model from Column 1 includes only fixed effects for college and no additional controls. Column 2 includes fixed effects for colleges and controls for demographic indicators including race/ethnicity, gender, and age. Column 3 includes college fixed effects, controls for demographic indicators and proxies for income including Pell and TAP Grant recipient status. Column 4 includes all the previous controls plus calculated math and English algorithm values, which serve as proxies for college preparedness.

***p < .01, **p < .05, *p < .10.

Appendix Table A.28

Effect of Program Assignment on Placement in College-Level English by Race/Ethnicity

Treatment Status and Model Indicators	(1)	(2)	(3)	(4)
Black students only				
Program assignment	0.382***	0.383***	0.384***	0.382***
	(0.042)	(0.042)	(0.042)	(0.039)
Control mean	0.413			
Observations	477	477	477	477
Hispanic students only				
Program assignment	0.328***	0.324***	0.323***	0.332***
	(0.035)	(0.035)	(0.035)	(0.033)
Control mean	0.541			
Observations	574	574	574	574
White students only				
Program assignment	0.220***	0.221***	0.218***	0.203***
	(0.026)	(0.026)	(0.026)	(0.024)
Control mean	0.604			
Observations	1,030	1,030	1,030	1,030
College fixed effects	YES	YES	YES	YES
Demographic indicators	NO	YES	YES	YES
Income indicators	NO	NO	YES	YES
College preparedness measures	NO	NO	NO	YES

NOTES: Robust standard errors shown in parentheses. The model from Column 1 includes only fixed effects for college and no additional controls. Column 2 includes fixed effects for colleges and controls for demographic indicators including race/ethnicity, gender, and age. Column 3 includes college fixed effects, controls for demographic indicators and proxies for income including Pell and TAP Grant recipient status. Column 4 includes all the previous controls plus calculated math and English algorithm values, which serve as proxies for college preparedness.

***$p < .01$, **$p < .05$, *$p < .10$.

Appendix Table A.29

Effect of Program Assignment on Placement in College-Level English by Pell Recipient Status

Treatment Status and Model Indicators	(1)	(2)	(3)	(4)
Pell recipients only				
Program assignment	0.307***	0.309***	0.308***	0.296***
	(0.024)	(0.024)	(0.024)	(0.023)
Control mean	0.485			
Observations	1,408	1,408	1,408	1,408
Non-Pell recipients only				
Program assignment	0.278***	0.275***	0.274***	0.276***
	(0.022)	(0.022)	(0.022)	(0.021)
Control mean	0.608			
Observations	1,340	1,340	1,340	1,340
College fixed effects	YES	YES	YES	YES
Demographic indicators	NO	YES	YES	YES
Income indicators	NO	NO	YES	YES
College preparedness measures	NO	NO	NO	YES

NOTES: Robust standard errors shown in parentheses. The model from Column 1 includes only fixed effects for college and no additional controls. Column 2 includes fixed effects for colleges and controls for demographic indicators including race/ethnicity, gender, and age. Column 3 includes college fixed effects, controls for demographic indicators and proxies for income including Pell and TAP Grant recipient status. Column 4 includes all the previous controls plus calculated math and English algorithm values, which serve as proxies for college preparedness.

***$p < .01$, **$p < .05$, *$p < .10$.

Appendix Table A.30

Effect of Program Assignment on Placement in College-Level English by Gender

Treatment Status and Model Indicators	(1)	(2)	(3)	(4)
Female students only				
Program assignment	0.309***	0.312***	0.312***	0.306***
	(0.024)	(0.024)	(0.024)	(0.023)
Control mean	0.535			
Observations	1,262	1,262	1,262	1,262
Male students only				
Program assignment	0.289***	0.289***	0.290***	0.284***
	(0.022)	(0.021)	(0.021)	(0.021)
Control mean	0.55			
Observations	1,570	1,570	1,570	1,570
College fixed effects	YES	YES	YES	YES
Demographic indicators	NO	YES	YES	YES
Income indicators	NO	NO	YES	YES
College preparedness measures	NO	NO	NO	YES

NOTES: Robust standard errors shown in parentheses. The model from Column 1 includes only fixed effects for college and no additional controls. Column 2 includes fixed effects for colleges and controls for demographic indicators including race/ethnicity, gender, and age. Column 3 includes college fixed effects, controls for demographic indicators and proxies for income including Pell and TAP Grant recipient status. Column 4 includes all the previous controls plus calculated math and English algorithm values, which serve as proxies for college preparedness.

***$p < .01$, **$p < .05$, *$p < .10$.

Appendix Table A.31

Effect of Program Assignment on Enrollment in College-Level English by Race/Ethnicity

Treatment Status and Model Indicators	(1)	(2)	(3)	(4)
Black students only				
Program assignment	0.326***	0.325***	0.324***	0.320***
	(0.043)	(0.043)	(0.043)	(0.042)
Control mean	0.409			
Observations	477	477	477	477
Hispanic students only				
Program assignment	0.263***	0.265***	0.264***	0.273***
	(0.038)	(0.038)	(0.038)	(0.037)
Control mean	0.515			
Observations	574	574	574	574
White students only				
Program assignment	0.171***	0.172***	0.170***	0.155***
	(0.028)	(0.028)	(0.028)	(0.027)
Control mean	0.563			
Observations	1,030	1,030	1,030	1,030
College fixed effects	YES	YES	YES	YES
Demographic indicators	NO	YES	YES	YES
Income indicators	NO	NO	YES	YES
College preparedness measures	NO	NO	NO	YES

NOTES: Robust standard errors shown in parentheses. The model from Column 1 includes only fixed effects for college and no additional controls. Column 2 includes fixed effects for colleges and controls for demographic indicators including race/ethnicity, gender, and age. Column 3 includes college fixed effects, controls for demographic indicators and proxies for income including Pell and TAP Grant recipient status. Column 4 includes all the previous controls plus calculated math and English algorithm values, which serve as proxies for college preparedness.

***p < .01, **p < .05, *p < .10.

Appendix Table A.32

Effect of Program Assignment on Enrollment in College-Level English by Pell Recipient Status

Treatment Status and Model Indicators	(1)	(2)	(3)	(4)
Pell recipients only				
Program assignment	0.272***	0.275***	0.275***	0.263***
	(0.025)	(0.025)	(0.025)	(0.024)
Control mean	0.446			
Observations	1,408	1,408	1,408	1,408
Non-Pell recipients only				
Program assignment	0.202***	0.195***	0.195***	0.196***
	(0.025)	(0.025)	(0.025)	(0.024)
Control mean	0.580			
Observations	1,340	1,340	1,340	1,340
College fixed effects	YES	YES	YES	YES
Demographic indicators	NO	YES	YES	YES
Income indicators	NO	NO	YES	YES
College preparedness measures	NO	NO	NO	YES

NOTES: Robust standard errors shown in parentheses. The model from Column 1 includes only fixed effects for college and no additional controls. Column 2 includes fixed effects for colleges and controls for demographic indicators including race/ethnicity, gender, and age. Column 3 includes college fixed effects, controls for demographic indicators and proxies for income including Pell and TAP Grant recipient status. Column 4 includes all the previous controls plus calculated math and English algorithm values, which serve as proxies for college preparedness.

***$p < .01$, **$p < .05$, *$p < .10$.

Appendix Table A.33

Effect of Program Assignment on Enrollment in College-Level English by Gender

Treatment Status and Model Indicators	(1)	(2)	(3)	(4)
Female students only				
Program assignment	0.233***	0.234***	0.234***	0.229***
	(0.026)	(0.026)	(0.026)	(0.025)
Control mean	0.484			
Observations	1,262	1,262	1,262	1,262
Male students only				
Program assignment	0.239***	0.239***	0.238***	0.233***
	(0.023)	(0.023)	(0.023)	(0.022)
Control mean	0.524			
Observations	1,570	1,570	1,570	1,570
College fixed effects	YES	YES	YES	YES
Demographic indicators	NO	YES	YES	YES
Income indicators	NO	NO	YES	YES
College preparedness measures	NO	NO	NO	YES

NOTES: Robust standard errors shown in parentheses. The model from Column 1 includes only fixed effects for college and no additional controls. Column 2 includes fixed effects for colleges and controls for demographic indicators including race/ethnicity, gender, and age. Column 3 includes college fixed effects, controls for demographic indicators and proxies for income including Pell and TAP Grant recipient status. Column 4 includes all the previous controls plus calculated math and English algorithm values, which serve as proxies for college preparedness.

***$p < .01$, **$p < .05$, *$p < .10$.

Appendix Table A.34

Effect of Program Assignment on Enrollment in and Completion of College-Level English by Race/Ethnicity

Treatment Status and Model Indicators	(1)	(2)	(3)	(4)
Black students only				
Program assignment	0.190***	0.183***	0.182***	0.176***
	(0.042)	(0.043)	(0.043)	(0.042)
Control mean	0.244			
Observations	477	477	477	477
Hispanic students only				
Program assignment	0.149***	0.149***	0.145***	0.154***
	(0.041)	(0.041)	(0.041)	(0.040)
Control mean	0.344			
Observations	574	574	574	574
White students only				
Program assignment	0.148***	0.146***	0.145***	0.130***
	(0.030)	(0.030)	(0.030)	(0.030)
Control mean	0.391			
Observations	1,030	1,030	1,030	1,030
College fixed effects	YES	YES	YES	YES
Demographic indicators	NO	YES	YES	YES
Income indicators	NO	NO	YES	YES
College preparedness measures	NO	NO	NO	YES

NOTES: Robust standard errors shown in parentheses. Completion is defined as earning a grade of C or better. The model from Column 1 includes only fixed effects for college and no additional controls. Column 2 includes fixed effects for colleges and controls for demographic indicators including race/ethnicity, gender, and age. Column 3 includes college fixed effects, controls for demographic indicators and proxies for income including Pell and TAP Grant recipient status. Column 4 includes all the previous controls plus calculated math and English algorithm values, which serve as proxies for college preparedness.

***$p < .01$, **$p < .05$, *$p < .10$.

Appendix Table A.35

Effect of Program Assignment on Enrollment in and Completion of College-Level English by Pell Recipient Status

Treatment Status and Model Indicators	(1)	(2)	(3)	(4)
Pell recipients only				
Program assignment	0.177***	0.177***	0.177***	0.167***
	(0.025)	(0.025)	(0.025)	(0.024)
Control mean	0.287			
Observations	1,408	1,408	1,408	1,408
Non-Pell recipients only				
Program assignment	0.124***	0.121***	0.121***	0.122***
	(0.027)	(0.027)	(0.027)	(0.026)
Control mean	0.399			
Observations	1,340	1,340	1,340	1,340
College fixed effects	YES	YES	YES	YES
Demographic indicators	NO	YES	YES	YES
Income indicators	NO	NO	YES	YES
College preparedness measures	NO	NO	NO	YES

NOTES: Robust standard errors shown in parentheses. Completion is defined as earning a grade of C or better. The model from Column 1 includes only fixed effects for college and no additional controls. Column 2 includes fixed effects for colleges and controls for demographic indicators including race/ethnicity, gender, and age. Column 3 includes college fixed effects, controls for demographic indicators and proxies for income including Pell and TAP Grant recipient status. Column 4 includes all the previous controls plus calculated math and English algorithm values, which serve as proxies for college preparedness.

***p < .01, **p < .05, *p < .10.

Appendix Table A.36

Effect of Program Assignment on Enrollment in and Completion of College-Level English by Gender

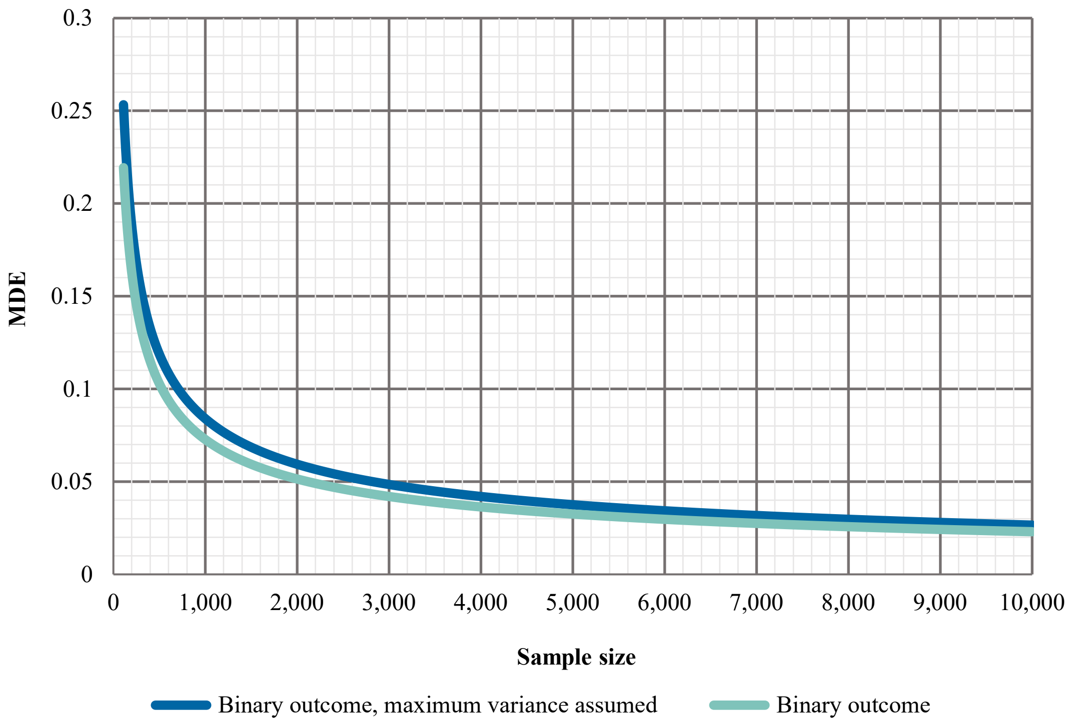
Treatment Status and Model Indicators	(1)	(2)	(3)	(4)
Female students only				
Program assignment	0.168***	0.169***	0.170***	0.165***
	(0.027)	(0.027)	(0.027)	(0.026)
Control mean	0.344			
Observations	1,262	1,262	1,262	1,262
Male students only				
Program assignment	0.139***	0.139***	0.139***	0.134***
	(0.024)	(0.024)	(0.024)	(0.024)
Control mean	0.333			
Observations	1,570	1,570	1,570	1,570
College fixed effects	YES	YES	YES	YES
Demographic indicators	NO	YES	YES	YES
Income indicators	NO	NO	YES	YES
College preparedness measures	NO	NO	NO	YES

NOTES: Robust standard errors shown in parentheses. Completion is defined as earning a grade of C or better. The model from Column 1 includes only fixed effects for college and no additional controls. Column 2 includes fixed effects for colleges and controls for demographic indicators including race/ethnicity, gender, and age. Column 3 includes college fixed effects, controls for demographic indicators and proxies for income including Pell and TAP Grant recipient status. Column 4 includes all the previous controls plus calculated math and English algorithm values, which serve as proxies for college preparedness.

***$p < .01$, **$p < .05$, *$p < .10$.

Appendix Figure A.1

Relationship Between Minimum Detectable Effect (MDE) and Sample Size: Binary Outcomes



NOTES: This figure plots the MDE for binary outcomes based on 80 percent power, a 5 percent significance level, and a two-tailed test, and assumes (conservatively) that the sample proportion randomly assigned for treatment is equal to 0.5. The figure presents two scenarios: (1) the top (dark) line calculates the MDE when $\pi = 0.5$, and (2) the bottom (light) line calculates the MDE when $\pi = 0.25$, where π is equal to the proportion of successful outcomes. (For binary outcomes, the MDE is symmetric at $\pi = 0.5$.)

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