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Should Students Assessed as Needing Remedial Mathematics Take College-Level Quantitative Courses Instead? A Randomized Controlled Trial

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Abstract

Many college students never take, or do not pass, required remedial mathematics courses theorized to increase college-level performance. Some colleges and states are therefore instituting policies allowing students to take college-level courses without first taking remedial courses. However, no experiments have compared the effectiveness of these approaches, and other data are mixed. We randomly assigned 907 students to (a) remedial elementary algebra, (b) that course with workshops, or (c) college-level statistics with workshops (corequisite remediation). Students assigned to statistics passed at a rate 16 percentage points higher than those assigned to algebra ($p<.001$), and subsequently accumulated more credits. A majority of enrolled statistics students passed. Policies allowing students to take college-level instead of remedial quantitative courses can increase student success.

Keywords: higher education, corequisite remediation, mathematics, randomized controlled trial
Should Students Assessed as Needing Remedial Mathematics Take College-Level Quantitative Courses Instead?

A Randomized Controlled Trial

Colleges in the United States assess a total of about 60% of their new freshmen as unprepared for college-level work (Grubb et al., 2011), most often in mathematics (Attewell, Lavin, Domina, & Levey, 2006). College policies usually require such students to complete remedial courses prior to taking college-level courses in the remedial courses’ disciplines, based on the purported theory that students need to pass the remedial courses in order to be able to pass the college-level courses. However, the percentage of students successfully completing remedial courses is low (Bailey, Jeong, & Cho, 2010). For example, at The City University of New York (CUNY) in fall 2014, 76% of new community college freshmen were assessed as needing remedial mathematics (CUNY, 2015b), and the pass rate in the highest-level remedial mathematics course across the community colleges was 38% (CUNY, 2015c). Further, at CUNY and nationally, many students, though assigned to remedial courses, wait to take them or never take them, delaying or preventing graduation (Bailey et al., 2010). It is therefore not surprising that students who enter college needing any remedial courses are less likely to graduate than are students who enter college with no such need (7% vs. 28% after three years at CUNY for students who entered CUNY community colleges in 2011; CUNY, 2015a).

Successful completion of mathematics remediation may be the single largest barrier to increasing graduation rates (Attewell et al., 2006; Complete College America, 2012).

Addressing the low pass rates in remedial mathematics courses could not only help overall graduation rates, it could also help close performance gaps. Students assessed as needing remediation are more likely to be members of underrepresented groups (Attewell et al., 2006).
Therefore low mathematics remediation pass rates contribute to the lower college attainment rates of members of underrepresented groups.

Various solutions to the low remedial course pass rates have been proposed at CUNY and nationwide. One alternative is having students address remedial needs in the summer before entering college. Although there is research supporting this type of approach (Douglas & Attewell, 2014), a randomized controlled trial found only modest positive effects in the first year following the summer program, and these positive effects did not persist (Barnett et al., 2012). Also, not all students can attend remedial courses the summer before college.

Another example is the CUNY Start program, in which students with multiple remedial needs postpone initial matriculation for one semester while engaging in full-time remediation. However, this program is only for students with severe remedial needs, not every student can devote an entire semester to remediation, and though its initial results are promising, there has not yet been an experiment evaluating it (Office of Academic Affairs, 2013).

The Carnegie Foundation for the Advancement of Teaching has promoted the use of Statway, which combines remedial mathematics with introductory statistics. A recent rigorous analysis supports Statway as increasing student success (Yamada, 2014). However, Statway can require a full academic year to obtain credits for one college-level course, and requires students to know much of elementary algebra. Further, the effects on enrollment of students being assigned to such a course are unknown.

Alternatively, some practitioners have advocated streamlining the remedial mathematics curriculum so that students learn only the remedial mathematics that they need for subsequent courses. However, only descriptive data are available for evaluating such approaches (Kalamkarian, Raufman, & Edgecombe, 2015).
As a form of streamlining, some colleges and states are instituting policies in which students assessed as needing remedial courses take college-level courses such as statistics instead, sometimes with additional academic support (e.g., Hern, 2012; Smith, 2015). Several theories have been suggested regarding why such approaches should be effective. First, at least some students assessed as needing remediation should perform satisfactorily in college-level courses because placement mechanisms are sometimes inaccurate, assessing some students as needing remediation even though their skills are sufficient for college-level work (Scott-Clayton, Crosta, & Belfield, 2014). Second, assigning a student to a remedial course may decrease that student’s motivation due to college graduation being more distant, and/or because the student already had an unpleasant experience with this course in high school, and/or because of the stigma of being required to take a remedial course (see, e.g., Logue, 1995; Bailey, 2009; Complete College America, 2011; Goldrick-Rab, 2007; Scott-Clayton & Rodriguez, 2012). Third, it has been proposed that students can pass college-level statistics more easily than remedial algebra because the former is less abstract and uses everyday examples (Burdman, 2013; Yamada, 2014).

There have been multiple attempts to compare the performance of students, assessed as needing remediation, who enroll first in remedial courses with the performance of students who enroll directly in college-level courses. Some of this research has used data obtained from naturally occurring variation in course placement, and some has used quasi-experimental methods such as propensity score matching and regression discontinuity. Results have been mixed. Some studies have found that students assessed as needing remediation perform better in college-level courses if they first take remedial courses (e.g., Bettinger & Long, 2009; Moss, Yeaton, & Lloyd, 2014). Others have found that such students do just as well or better in
Should Students Assessed as completing college if they skip remediation (e.g., Boatman, 2012; Calcagno & Long, 2008; Clotfelter, Ladd, Muschkin, & Vigdor, 2015; Jaggars, Hodara, Cho, & Xu, 2015; Martorell & McFarlin, 2011). Still others have found both types of results (e.g., Melguizo, Bos, & Prather, 2011; Wolfle & Williams, 2014).

The term mainstreaming has been used to describe placing students assessed as needing remediation directly into a college-level course (see, e.g., Edgecombe, 2011; such students are not necessarily mixed within the classroom with other students, as occurs with mainstreaming in K-12 education). There have been several apparently successful programs for mainstreaming college students assessed as needing remediation, sometimes with additional instructional support (e.g., an English program at Community College Baltimore County, and a mathematics program at Austin Peay State University; Jones, 2014).

The concern with all of these studies is that, because none of them have used experimental methods (i.e., randomized controlled trials), there could have been uncontrolled, unmeasured differences in some variables across the groups of students exposed to different treatments (as in some propensity score matching studies), and/or the findings could be limited to a narrow range of students (as in some regression discontinuity studies). For example, student motivation, which is difficult to measure, may vary across groups of students who are not randomly assigned to remedial and college-level courses. Such differences could help explain the inconsistent results across studies.

Our research’s purpose was therefore to use a randomized controlled trial to examine a promising approach for overcoming the block to college progress posed by mathematics remediation: mainstreaming. The experiment compared academic performance (pass rates) in remedial elementary algebra with a college-level course (statistics) for students assessed as
needing remedial elementary algebra. Most (55.69%) of the students who took the college-level course (statistics) passed that course. Further, students assigned to statistics passed at a rate that was 16 percentage points greater, and subsequently accumulated more credits, than students assigned to elementary algebra. Students do not first have to pass remedial mathematics in order to pass college-level statistics, and policies placing students assessed as needing remedial mathematics directly into college-level quantitative courses can increase student success.

**Design of Present Research**

For purposes of sample size and generalizability, we conducted the experiment at three CUNY community colleges (Colleges A, B, and C), one each in the boroughs of the Bronx, Manhattan, and Queens. At all three, we randomly assigned students assessed as needing remedial elementary algebra to one of three fall 2013 course types: (a) traditional, remedial, noncredit, elementary algebra (Group EA), (b) that course with weekly workshops (Group EA-WS), or (c) college-level, credit-bearing statistics with weekly workshops (Group Stat-WS).

Additional academic support has been termed supplemental or corequisite instruction (Bueschel, 2009; Complete College America, 2016). The present experiment used it for three reasons: (1) Evidence suggests that such support tends to increase students’ grades (e.g., Bettinger & Baker, 2014; Bowles, McCoy, & Bates, 2008), (2) CUNY policy requires that students assessed as needing remediation be provided with an intervention addressing that need, and (3) the additional support helped allay concerns that placing students assessed as needing remedial elementary algebra directly into college-level statistics with no additional support would result in even lower pass rates than those for elementary algebra.

These three groups allowed us to examine: (1) the effects of adding workshops to elementary algebra by comparing Groups EA and EA-WS (we could not assess the effects of
Should Students Assessed as adding workshops to statistics given that we could not offer statistics without workshops; (2) the effects of exposing students to statistics as opposed to elementary algebra, each with workshops (by comparing Groups EA-WS and Stat-WS); and (3) the effects of placing students into statistics with workshops as compared to a traditional remedial course (by comparing Groups EA and Stat-WS). We could also compare the performance of the three experimental groups with the performance of all students taking elementary algebra and statistics in fall 2012, allowing us to compare our students’ performance with typical norms.

We hypothesized that the EA group would pass at the typical elementary algebra rate (fall 2012, 37%), that the EA-WS group would pass at a higher rate due to the positive effects of the workshops, and that the Stat-WS group would pass at a rate at least as high as the EA group, although lower than the typical rate for statistics (fall 2012, 69%; because the Stat-WS students would be taking a college-level quantitative course without the assumed benefits of first taking elementary algebra, but with the benefits of the workshops and of being assigned to a college-level course). We also hypothesized that a higher pass rate would be associated with more credits accumulated in the year following the experiment, because students who passed would have an opportunity to take more credit-bearing courses.

**Participant Recruitment**

During the summer prior to the fall 2013 semester, all eligible students at each participating college were notified of the research via email and during in-person orientation sessions for new students. At the orientation sessions, potential participants were given a flyer and a consent form stating the requirements for study participation (Appendixes A and B contain the text of College A’s flyer and consent form): minimum age 18, first-time freshman, intending to major in disciplines that did not require college algebra, and assessed as needing elementary
algebra. Participants could obtain a $40 Metrocard for New York City public transportation if they were enrolled in their assigned research sections after the end of the course drop period (73% of participants retrieved them), and a $10 Metrocard after the semester ended (35% retrieved them). We instructed recruiters to be neutral when describing the different treatment conditions to potential participants. However, recruitment flyers did state: “Benefits [of participation] include: A one-in-three chance to skip remediation in math and go directly to an enhanced college-level mathematics course.”

A total of 907 eligible students consented to the experiment (see Appendix C for the relevant power analysis). As soon as the consent form was signed, research personnel randomly assigned these students to one of the three course types (Groups EA, EA-WS, and Stat-WS) using random number tables created with MS Excel, and informed students of their assignments, including their course sections. Recruitment took place during the three months before the start of the semester. As of the official course census date (approximately two weeks after the start of the semester, the day after the end of the drop period), 717 of these consenting students were enrolled in their assigned research sections and were designated the experiment’s participants. Figure 1, Table 1, and Table 2 provide information about all of the students involved in the experiment.

Figure 1 shows the flow of target students through each stage of the experiment. There was an overall attrition rate of 21% (190 students) between when students were randomized and the semester’s course census date. Attrition was significantly higher in Group EA-WS than in Groups EA or Stat-WS (Table 3). A Tukey post-hoc test comparing attrition in Groups EA and Stat-WS was not significant, but tests comparing attrition between Group EA-WS with Groups EA and Stat-WS were significant ($p=.010$ and $p=.005$, respectively). In contrast, there were no
significant differences among the three groups in the percentages of students who withdrew during the semester. The relatively large attrition in Group EA-WS meant that we needed to consider the possibility that, although students were randomly assigned to Group EA-WS, the actual Group EA-WS participants did not constitute a random sample of those who consented. However, note that, as indicated by Figure 1 and Table 3, the attrition among the EA-WS students (28%) was nevertheless less than the percentage of nonconsenting students who, although assigned to elementary algebra, did not take it (40%; because they never enrolled at CUNY, because their mathematics placement level changed, because they did not attend orientation, or because they avoided taking elementary algebra).

Of the 190 students who signed the consent form but who were not enrolled in their research sections on the fall 2013 census date (“noncompliers”), 57.90% were not enrolled in any college—CUNY or nonCUNY—that semester (National Student Clearinghouse data; an example of what has been called “summer melt,” Castleman & Page, 2014). Consistent with the attrition data reported earlier, the largest proportion, 45.46%, of these 110 students consisted of students who had been randomly assigned to Group EA-WS.

A total of 34 noncompliers across the three groups enrolled in nonresearch sections of elementary algebra in the fall of the experiment. No student assigned to a research section attempted to attend a different research section. Although only research participants were supposed to enroll in research sections, five nonresearch students enrolled in research sections (four total in three EA-WS sections, and one in a Stat-WS section). We excluded these five students from all analyses.

Table 1 shows the variables for which we had data for both the 717 participants and the 190 noncompliers. There were no significant differences between these two groups except that,
on average, noncompliers agreed to participate in the experiment significantly earlier than participants. These results are consistent with previous findings that students who agree early to participate in research are less likely to participate. Early-consenting students may be more likely to encounter work or other time conflicts with scheduled research (Watanabe-Rose & Sturmey, 2008).

To examine whether the students who participated in the treatments were representative of all students assessed as needing elementary algebra, we also compared participants with nonconsenters who took nonresearch sections of elementary algebra during the same semester as the experiment (60% of all nonconsenters; see Table 1). The only significant difference between these two groups is in the proportion of underrepresented students (p<.001), although underrepresented students constitute a substantial majority of both groups. However, these two groups may have differed on other (unmeasured) variables given that one group consented to be in our experiment, an experiment that involved a class taught during the day, and the other group did not.

**Participant Treatments**

Research personnel recruited instructors and selected the course sections in which the participants would enroll. There were 12 instructors, four at each of the three colleges. The instructors had to be full-time, willing to teach two sections of elementary algebra and one of introductory statistics, and, preferably, have taught both subjects before (three of the 12 instructors had only taught elementary algebra before). In order to be able to assess instructor effects and to balance these effects across treatments, each instructor taught one section of each of the three course types: EA, EA-WS, and Stat-WS (Weiss, 2010). Thus there were 12 sections each of EA, EA-WS, and Stat-WS. This meant that the instructors had to be informed about the
basic structure of the experiment, including during a 6-hour orientation session that they attended prior to the experiment (Appendix D provides an example of a faculty orientation agenda). The instructors were told that the researchers believed that “at least some students assessed as needing elementary algebra will successfully pass statistics without taking elementary algebra.” Faculty were not given the experiment’s research hypothesis and were never told that the researchers hoped that statistics would have at least the same pass rate as elementary algebra.

The instructors helped ensure that the research was conducted properly. For example, at each college they ensured that all research sections of statistics used the same syllabus (there was already a departmental common syllabus for elementary algebra at each college). Each instructor also met monthly with research personnel and weekly with the workshop leaders of that instructor’s two sections that included workshops. During the weekly sessions, the instructors gave their workshop leaders assignments and exercises for the participants to work on during the workshops and as homework. Research personnel told the instructors to teach and grade the research sections as they would ordinarily. Each instructor was paid $3,000 for his/her participation.

Research personnel recruited the workshop leaders. Qualifications included advanced undergraduate status at or recent graduation from CUNY, successful completion of the material to be covered in the leader’s workshops, a recommendation from a mathematics faculty member, and a satisfactory personal interview. A total of 21 workshop leaders were selected for the 24 research sections that had associated weekly workshops (three workshop leaders each led the workshops for two sections). They were paid at the rate of $14 per hour. Before the experiment began, the workshop leaders had 10 hours of training concerning the experiment and how to conduct their workshops. During the experiment’s semester, the workshop leaders met monthly
with research personnel and also discussed together on social media their concerns and suggestions about conducting their workshops. Workshop leaders attended their section’s regular class meetings.

Section size did not vary significantly by group (means and 95% CIs: Group EA 20.33 [17.51, 23.15], Group EA-WS 18.92 [16.16, 21.67], Group Stat-WS 20.50 [18.67, 22.3], $F [2,33]=0.58, p=.56$). Elementary algebra sections and any associated workshops covered topics such as linear equations, exponents, polynomials, and quadratic equations (Appendix E provides a sample syllabus). Statistics sections and associated workshops covered topics such as probability, binomial probability distributions, normal distributions, confidence intervals, and hypothesis testing (Appendix F provides a sample syllabus). If students in statistics sections needed to review certain algebra concepts in order to understand a particular statistics topic, such as using variables in equations and different types of graphs, the workshop leader would cover that topic in the workshop. Course sections lasted three to six hours per week, depending on the college.

All workshops occurred weekly, lasted two hours each, and had the same structure: 10-15 minutes of reflection by students on what they had learned recently in class and what they had found difficult, then approximately 100 minutes of individual and group work on topics students had found difficult, and a final five minutes of reflection by students on the workshop’s activities and whether the students’ difficulties had been addressed. Research personnel informed all students enrolled in research sections with workshops that they were required to attend the workshops, and that if they missed more than three they would have to meet with the instructor. Only students in EA-WS and Stat-WS sections could attend those sections’ workshops.

At the end of the semester, EA and EA-WS participants took the required CUNY-wide
elementary algebra final examination and received a final grade based on the CUNY-wide elementary algebra final grade rubric. Instructors graded their Stat-WS participants at their discretion using the common syllabus for that college. All outcomes other than a passing grade, including any type of withdrawal or a grade of incomplete, were categorized as not passing.

All participants who passed were exempt from any further remedial mathematics courses and were eligible to enroll in introductory, college-level (i.e., credit-bearing) quantitative courses and, in the case of Stat-WS participants, to enroll in courses for which introductory statistics is the prerequisite. A passing grade in Statistics satisfied the quantitative category of the CUNY general education curriculum. Participants who did not pass had to enroll in traditional remedial elementary algebra and pass it before taking any college-level quantitative courses. Stat-WS participants were informed that if they did not pass, a failing grade would not be included in their GPAs.

To check course progress, research personnel observed three regular class meetings of each section, as well as at least three workshops for each section of Groups EA-WS and Stat-WS. Sections were one or two weeks behind the syllabus in 25.93% of the class meetings and 27.40% of the workshops observed. In such situations, research personnel reminded the relevant instructor or workshop leader to follow the syllabus as consistently as possible.

Participants completed a mathematics attitude survey at the semester’s start and end (based on Korey, 2000), and a student satisfaction survey at the semester’s end. These pencil-and-paper surveys primarily consisted of 7-point Likert scales. The mathematics attitude survey consisted of 17 questions covering the following four domains: perceived mathematical ability and confidence (“Ability”), interest and enjoyment in mathematics (“Interest”), the belief that mathematics contributes to personal growth (“Growth”), and the belief that mathematics
contributes to career success and utility (“Utility”). The student satisfaction survey asked about a student’s activities during the semester, e.g. whether the student had gone for tutoring (available to all students independent of the experiment), and about a student’s satisfaction with those activities.

**Method of Analysis for Treatment Effects**

Given that students were randomly assigned to treatments, simple comparisons of course outcomes for all 907 students randomized to the three groups can identify the relative treatment effects. Intent-to-treat (ITT) analysis compares mean outcomes of groups as randomized, without regard to attrition and other forms of deviation from protocol, thus providing an unbiased estimate of the treatment effect. We compared our two treatment groups, EA-WS and Stat-WS, with Group EA. We estimated the ITT effect using Equation 1:

\[
\ln \left( \frac{\hat{p}_i}{1-\hat{p}_i} \right)_i = \delta + \beta_1 \times \text{STATS}_i + \beta_2 \times \text{EAWORK}_i + \varepsilon_i ,
\]  

in which \( \ln \left( \frac{\hat{p}_i}{1-\hat{p}_i} \right)_i \) is the log odds of a positive outcome for student \( i \), \( \delta \) is the equation constant, STATS represents whether the student was randomized into group Stat-WS, EAWORK whether the student was randomized into group EA-WS, \( \beta_1 \) and \( \beta_2 \) are coefficients, and \( \varepsilon_i \) is an error term.

The outcomes of interest are, first, whether a student passed his or her assigned course, and, second, the total number of credits that a student had earned by one calendar year following the experiment’s end. The latter analysis used an OLS regression in which \( Y_i \) was equal to credits earned.

In order to explore further the relationships between passing the assigned course and other variables, we also fit a model that included a vector of covariates (algebra placement test score, gender, high school GPA, number of days to consent, and controls for missing values). This vector of covariates is represented by \( X \) in Equation 2:
\[
\ln \left( \frac{\hat{p}_i}{1-\hat{p}_i} \right) = \delta + \beta_1 \times \text{STATS}_i + \beta_2 \times \text{EAWORK}_i + bX_i + \varepsilon_i , \tag{2}
\]
with terms defined as in Equation 1 plus addition of the coefficient \(b\). We did not include the prealgebra (arithmetic) placement score as a covariate because it did not add any explanatory power. We incorporated additional control variables in a subsequent analysis of the 717, but among all students randomized we have only a limited set of covariates.

Given attrition varied by group, we also determined estimates of the effect of treatment on the treated (Treatment on Compliers, or TOC) by using Angrist, Imbens, and Rubin’s (1996) instrumental variables approach. Our design meets the assumptions necessary for this approach because (a) we randomized students into groups, (b) random assignment was highly correlated with receiving treatment, and (c) those assigned to the control group (Group EA) had no ability to enroll in a different group. Instrumental variables analysis has two steps: regressing random assignment on the actual receipt of the treatment, then using the predicted values from the first step in a second regression model predicting outcome variables (here, passing the assigned course). We estimated TOC effects with the same covariates used in the ITT analysis.\(^2\)

**Results of Analysis for Treatment Effects**

**ITT and TOC**

Tables 4 (passing the assigned class) and 5 (total credits accumulated) report the results using ITT and TOC methods. Table 4’s ITT estimates with no covariates show that students in Group EA-WS were not significantly more likely to pass than those in Group EA (\(p = .48\)). Those in Group Stat-WS were significantly more likely to pass than those in Group EA by a margin of 16 percentage points, and than those in Group EA-WS by 13 percentage points. When we add covariates to the ITT equation (Equation 2), there is again no significant difference between groups EA and EA-WS (\(p=.14\), but students in the Stat-WS group were significantly
more likely to pass than EA students by 14 percentage points and than EA-WS students by 11 percentage points. TOC estimates show similar results.

Table 5 shows that the Stats-WS students’ enhanced academic success lasted beyond the experiment’s semester (beyond the grading of the experiment’s instructors), as evidenced by the Stat-WS students’ greater credit accumulation rates. ITT tests, both with and without covariates, and with and without statistics credits included, are significant ($p<.001$). One year after the end of the experiment, the Stat-WS participants had increased their mean total accumulated credit advantage from 2.38 (8.26 vs. 5.88) to 4.00 (21.71 vs. 17.71) in comparison to the EA participants. A higher percentage of the Stat-WS participants was enrolled (66%) than of the EA participants (62%) in fall 2014, but this difference is not significant.

We also explored the performance of the three groups in CUNY’s nine general education course categories through one calendar year after the end of the experiment (the end of fall 2014). Among all 907 randomly assigned students, as expected, the Stat-WS students were significantly more likely to have satisfied the quantitative category than students in the other two groups (.48[.42,.54] compared to .22[.17,.27] and .21[.17,.26] for Groups EA and EA-WS, $p<.001$ for both comparisons), and as likely to have satisfied the two other STEM and six nonSTEM categories than had students in the other two groups (see Appendix G). Stat-WS students made progress in satisfying their general education requirements in science and nonSTEM disciplines despite not having been assigned to elementary algebra.

**Course Success Among Participants**

Figure 2 shows the overall pass rates for each of the three groups of participants (EA, EA-WS, and Stat-WS) and compares them to the historical pass rates for these courses in fall 2012. The pass rate for Group EA-WS (44.93%), which was 5.59 percentage points higher than
that of Group EA (39.34%), is also higher than that of students who took elementary algebra at the three colleges in fall 2012 (36.80%).\(^3\) In contrast, the pass rates for Group EA (39.34%) and for students who took elementary algebra in fall 2012 (36.80%) are similar. Group Stat-WS passed at a lower rate (55.69%) than did students who took introductory statistics at the three colleges in fall 2012 (68.99%). However, as demonstrated in Figure 2, if the Group Stat-WS sample is restricted to participants who received relatively high scores on the placement test, the mean pass rate (67.62%) is similar to that of the previous year’s statistics students (68.99%). Colleges can place into statistics students just below the cut off for elementary algebra without any diminution in the typical statistics pass rate.

Having established a significant effect of the treatment on passing using the ITT and TOC analyses, we utilized logistic regression to further investigate predictors of participants passing assigned courses. The main independent variable was a set of dummy variables indicating treatment status, with Group EA as the omitted reference group. For ease of interpretation, Table 6 reports the results of the logistic regression as average marginal effects rather than as odds-ratios.\(^4\) The largest effect size was that of the treatment—being placed in Group Stat-WS. As noted above, we find no significant difference between Group EA and Group EA-WS in the probability of passing (\(p=.097\)), but the difference between Groups EA-WS and Stat-WS is significant (\(p=.031\)), as is the difference between Groups EA and Stat-WS (\(p<.001\)). When controlling for all other variables, there is a significant difference of almost 17 percentage points between students in Group Stat-WS and Group EA. Being enrolled in Stat-WS is associated with students’ probability of passing more than the increase associated with a one-standard-deviation increase in the Compass algebra score. Some covariates showed significant effects: Students with higher algebra placement scores and higher high school GPAs
were more likely to pass, and students whose first language was English were less likely to pass.

No interactions between student demographic variables and treatment status were significant. However, given that the purpose of placement tests is to place students in courses in which they are most likely to be successful, the widespread use of these tests, and their significant cost (Rodríguez, Bowden, Belfield, & Scott-Clayton, 2015), as well as the fact that we had placement test scores for most of the participants, we particularly examined the relationship between placement test score and passing. Table 6 shows that algebra placement test z-score is a strong predictor of passing with all participants combined. Figure 3 shows, for each group separately, the relationship between these scores and the probability of passing (a version of this Figure based on a nonlinear—quadratic—form is shown in Appendix H). For this analysis we focused only on those participants who had placement scores, and controlled for the same covariates included in the logistic regression model reported above in Table 6. Given that the line for Group Stat-WS is consistently higher than that for Group EA, students with any placement test algebra score are more likely to pass if they enroll in introductory statistics with a weekly workshop as opposed to traditional elementary algebra. It should also be noted that, in this sample, even students with average placement test scores have a better than 50% chance of passing statistics with a weekly workshop. Finally, the fact that the line for Group EA-WS is consistently higher than the line for Group EA supports the hypothesis that the workshops did help students to pass elementary algebra.

Figure 4 summarizes the quantitative-skills and quantitative-course status of the 717 participants in the three groups as of one year after the end of the experiment: 57.32% of the Stat-WS students had passed a college-level quantitative course (all but two of them by passing statistics in the fall of 2013), while 37.80% still had remedial need. In contrast, only 15.98% of
the EA students had passed a college-level quantitative course and 50.00% still had remedial need.

**Additional Effects**

Neither an instructor’s tenure status nor experience was significant in the logistic regression (see Table 6). To test further instructors’ impact on course outcomes, we used a mixed-effects logit regression model with instructor as the random effect (see Appendix I). The results showed that instructor assignment affected students’ probability of passing. However, there was still an effect of treatment group, again indicating that, across classrooms and instructors, Stat-WS students were more likely to pass. A log-likelihood test comparing a standard logistic regression with the mixed-effects model showed the latter to fit the model significantly better, $\chi^2(1)=5.33, p=.011$. There was no differential effect of treatment status as a function of instructor demographic characteristics.

Being enrolled in Group Stat-WS may have particularly enhanced participants’ attitudes about mathematics. The three groups’ participants did not significantly differ on any of the four domains measured by the pre-course student mathematics attitude survey. However, comparing this survey’s pre- and post-course results among the 338 participants who completed both, Group Stat-WS participants showed significant increases by the end of the semester on the Interest, Growth, and Utility domains. In contrast, Groups EA and EA-WS participants showed increases only in the Interest domain (Table 7). However, conclusions should be made with caution given that the response rates were around 50%, and that, across all three treatments combined, the pass rate of participants who filled out both the pre- and the post-mathematics attitude surveys was 68%, as compared to 28% for other participants.

Two aspects of student behavior could help to explain the three groups’ pass rates
differences. First, although there were no significant differences among the groups in terms of reported use of the tutoring available to all students, the post-course student satisfaction survey showed that EA-WS and Stat-WS participants were more likely to participate in self-initiated study groups than were EA participants (percentages of EA, EA-WS, and Stat-WS groups who engaged in a self-initiated study group: 41.98% [33.42, 50.55], 61.11% [52.48, 69.74], and 67.38% [59.54, 75.21], respectively; $F[2, 395] = 9.97, p < .001$). (Again, these results should be cautiously interpreted due to low survey response rates, around 50%.) Second, Stat-WS participants were more likely to attend their workshops (71.99%) than were EA-WS participants (65.04%; 95% CI for the difference in the percentage of workshops attended by Stat-WS and EA-WS participants is [-12.13, -1.76]; $t[471] = -2.63, p = .009$). These behavior differences may be course effects, not a priori causes of higher pass rates for Groups EA-WS and Stat-WS, indicating the positive motivational effects of being assigned to a college-level course.

Another possible reason for the higher pass rates in Group Stat-WS is that, despite randomization, the groups might have differed in terms of student characteristics that can affect passing. However, there is no compelling evidence that this occurred. Table 2 shows no significant differences among the three groups on any of the measured variables.

Yet another possible reason for the higher pass rates in Group Stat-WS is that, due to the random assignment methods, the Stat-WS students may have felt that they won a lottery and therefore been more motivated. Any such effect, if it existed, would have had to have continued into the year after the experiment was over, when the credit gap between Groups EA and Stat-WS widened.

Still another possible reason for the higher pass rate in Group EA-WS than Group EA, and the highest pass rate in Group Stat-WS, is that, although each instructor taught one section of
each course type, perhaps the instructors graded these courses differently. Given that elementary algebra and introductory statistics are qualitatively different courses, it is not possible to compare their grading directly. However, given that the experiment’s purpose was to compare student success rates in typical remedial mathematics and introductory statistics courses, a more useful question is whether the grading criteria used by the experiment’s instructors were similar to when these courses were usually taught. Nine pieces of evidence suggest that the results were due to group assignment, and not due to changes in the instructors’ grading practices.

First, all 12 of the instructors had taught elementary algebra before, nine had previously taught Introductory Statistics, and all were told by the researchers to teach as they usually did. Second, there were no significant relationships between participants passing and instructors’ tenure status, total years of experience, or experience teaching statistics (Table 6). Third, as shown by the results of the mixed-effects logistic regression and Table 6, the stronger effect size was for group assignment, not instructor. Fourth, all sections of elementary algebra across CUNY are standardized in terms of topics, a common final exam, and a common final grade rubric. For introductory statistics, all sections at the community colleges cover the same topics, and the experiment’s instructors at each college taught from a common syllabus. Fifth, there were no significant differences in percentage passing by college (Table 6). Sixth, despite the use of a randomized controlled trial with monetary incentives for participation, as described previously, the pass rate for Group EA was similar to that of students who took elementary algebra one year earlier, and the pass rate of Group Stat-WS was lower than that of students who took statistics one year earlier (students who were either exempt from remedial mathematics, or who had previously passed remedial mathematics and were in at least their second semester at CUNY). Seventh, a subset of Stat-WS participants with Compass scores close to the criterion for
mathematics remediation exemption passed statistics at a rate similar to that of statistics students with no remedial need (the two most right-hand bars in Figure 2). Eighth, as indicated earlier, the higher pass rates of Stat-WS students are consistent with indications that these students were more motivated. Ninth, as also discussed earlier, the Stat-WS students’ enhanced academic success lasted beyond the grading of the experiments instructors, with the Stat-WS students continuing to accumulate more credits than students in the other two groups during the calendar year following the experiment.

**Discussion and Policy Implications**

The results showed that the Stat-WS students passed statistics at, not the hypothesized same rate as the elementary algebra students, but at a significantly higher rate than did the EA and EA-WS students. The higher pass rate for statistics with additional support as compared to elementary algebra was robust across multiple types of analyses, colleges, and instructors. By one year after the experiment was over, the Stat-WS students had also satisfied the same number of general education science categories and had continued to accumulate more credits than the students in either of the other two groups. Students assessed as needing elementary algebra do not first need to pass that course in order to pass a college-level quantitative course and to be successful in college, at least not if that college-level course is introductory statistics with weekly workshops.

The mainstreaming/corequisite remediation approach has the potential to positively affect the academic progress of many thousands of college students. At CUNY in fall 2012 alone, 7,675 new students were initially assessed with a placement of remedial elementary algebra. In order to complete statistics within two semesters of entry, such students would have to pass elementary algebra in the fall (the actual pass rate is 37%), return in the spring (the overall
retention rate for freshmen from fall to spring is 84%), and then take and pass statistics in the spring (CUNY statistics students who have previously passed elementary algebra have a 68% statistics pass rate). Even if we were to assume that all fall students who pass elementary algebra are retained for the spring, and that all such students take statistics that spring semester, the probability of completing statistics within two semesters for these students is therefore only .37 times .68, i.e., .25. In contrast, 55.69% of the Stat-WS participants passed statistics in their first semester, and of those who did not, more might pass it in their second semester if permitted to attempt it again. This suggests that, of students entering CUNY just in fall 2012, at least 2,379 more students would pass statistics by the end of their second semester at CUNY if they took a statistics-with-workshops quantitative path rather than the traditional elementary algebra path (4,298 vs. 1,919 students completing statistics within two semesters). These benefits for thousands of students accrue with a 55.69% pass rate in statistics. Should that pass rate be increased, e.g. by focusing the workshops on the most useful content, even more students could benefit in terms of satisfying CUNY’s general education quantitative requirement and making progress in college.

The degree to which these implications would apply nationally remains to be explored; we do not know precisely how representative the three participating colleges are of all colleges, or even community colleges, across the United States. Three different community colleges were involved in the present experiment, but all used the CUNY algebra placement cut score of 40 for exemption from (remedial) elementary algebra. In contrast, a national survey of colleges and universities (not just community colleges) found a mean cut score of 49 (National Assessment Governing Board, 2011). However, Figure 3 suggests that the remediation used here would benefit students with a wide range of Compass scores, and there have been many descriptions
Our results demonstrate that mainstreaming/corequisite remediation can help to decrease performance gaps: our student sample was diverse and our findings did not differ by race (Table 6). In addition, the statistics course pass-rate advantage in the present experiment exists for students with a wide variety of placement test scores (Figure 3). Whether their placement test scores accurately reflect their abilities or not, students placed into statistics with workshops rather than elementary algebra should be more likely to pass a college-level quantitative course and complete college. Further, our data suggest that students whose placement is elementary algebra will not only be more likely to pass but will have a more positive attitude toward mathematics if they first take statistics than if they first take elementary algebra. Thus taking statistics first might be appropriate for students intending to become STEM majors, not just other majors. Taking statistics first might encourage a student to remain, as well as to become, a STEM major.

Our findings are inconsistent with the purported theory underlying many colleges’ policies requiring students to pass remedial courses prior to taking college-level courses. Instead, the results support state and college policies, instituted to increase college graduation rates, that allow, or require, placement of students assessed as needing remedial mathematics instead into college-level quantitative courses.

Our data are consistent with some of the theories regarding why placement into college-level courses can enhance student performance. For example, the evidence supports the theory that the STAT-WS students would be more motivated than the other students. The higher workshop attendance rate, the self-reported higher study-group rate, and the greater increase in
positive attitudes towards mathematics among the Stat-WS participants all support this theory.

Most participants in our EA and EA-WS groups ended the semester having spent 3 hours (or more) per week of course time, and the resulting tuition and financial aid, with no resulting progress towards their degrees, and still needing to pass a remedial course, but most of the participants in our Group Stat-WS ended the semester with three credits towards their degrees and satisfaction of their college’s general education quantitative requirement. Thus students in Group Stat-WS who passed were two courses closer to their degrees than were students in any of the groups who failed. Such degree progress contributes to what has been termed academic momentum (Adelman, 2006; Attewell, Heil, & Reisel, 2012), in addition to decreasing time-to-degree (Bowen & McPherson, 2016), both of which have been described as critical to college completion. The increased total cumulated credits advantage of the Stat-WS compared to the EA participants one year after the experiment was over supports the hypothesis that mainstreaming increased the long-term academic momentum of the Stat-WS students.

Other findings from this experiment provide some guidance regarding the usefulness of workshops. The evidence regarding whether the workshops helped the elementary algebra students pass is mixed. The ITT and TOC comparisons of Groups EA and EA-WS were not significant (Table 4). However, the EA-WS participants consistently passed at a higher rate than the EA participants (Figures 2 and 3). Further, in accordance with predictions, EA participants passed at a rate similar to that of elementary algebra students one year earlier, but EA-WS participants passed at a higher rate than did elementary algebra students one year earlier.

Prior research and the present Group EA vs. Group EA-WS comparisons only suggest that the workshops improved the statistics pass rates. Due to CUNY policy participants could not be placed into statistics without workshops. Therefore it is not possible to determine from
the present experiment how much of the greater pass rate by the Stat-WS students was due to the workshops and how much was due to the students being enrolled in a college-level statistics course.

We also do not know what the pass rate would have been had our participants been randomly assigned to college algebra with workshops. A direct comparison of student performance in such a course vs. statistics with workshops could help determine whether the effect of mainstreaming with workshops is course specific.

An unanticipated and concerning finding is that there was differential attrition for the three groups (see Table 3), suggesting that assigning students to a time-consuming remedial course (here Group EA-WS) may discourage them from attending college altogether. This possibility should be examined in future research. This finding also indicates that, when comparing performance in different courses, researchers should carefully examine the pre-course attrition rates, and not just performance during the courses. Note that Group EA-WS students were required to attend class five-six hours per week just to address their remedial need, in comparison to three-four hours for Group EA, and five-six hours for Group Stat-WS to address their remedial need but to also receive three college-level general education credits. Thus Group EA-WS was most distant in time from the goal of graduation, and was probably least motivated to attend the experiment’s assigned course and possibly also college.

Although the results of the present experiment show that students assigned to remedial mathematics can progress more quickly towards their degrees if they instead take introductory statistics with workshops, degree progression is not the only consideration in setting remediation policy. The participants in Group Stat-WS were only taught elementary algebra material to the extent that such material was needed to understand the statistics material. Whether students
should be graduating from college having learned statistics but without having learned all of elementary algebra is one of the many decisions that a college must make regarding which particular areas of knowledge should be required for a college degree. Views can differ as to which quantitative subjects a college graduate should know. However, it is clear that passing elementary algebra is not necessary in order to pass introductory statistics with weekly workshops. Therefore if a college or state deems introductory statistics to be necessary for a degree, it does not necessarily need to also require the usually precollege (i.e., remedial) course of elementary algebra. For a college or state to require all students to pass elementary algebra first, in addition to completing the credits needed for their degrees, can be an extra cost for students, colleges, and taxpayers, funds that could be spent on other college courses and programs. That extra cost, as well as educational goals, should be taken into account when higher education policy decisions are made. College communities, and our society, must decide whether the extra cost is worth the results.
Footnotes

1 Colleges usually designated a student as needing elementary algebra if that student lacked both a mathematics SAT score of at least 500, and a New York State mathematics Regents score of at least 80 along with passing grades in three units of high school college preparatory mathematics, but had received a passing score (35 or higher) on the prealgebra portion of the CUNY mathematics placement examination (the ACT Compass test) along with a nonpassing score (less than 40) on the elementary algebra portion.

2 We used the `ivprobit` command in the Stata software package to compute the TOC estimates.

3 The pass rates among the groups of participants (Figure 2) are higher than those in the ITT and TOC estimates (Table 4) because consenting students who did not participate in the experiment generally left college or did not take elementary algebra (Figure 1), and thus were coded as not passing.

4 Average marginal effects were obtained using the `margins, dydx` command in the Stata 13 software package.

5 Mixed effects models are alternatively known as Hierarchical Linear Models (HLM). We also conducted logistic regression with instructor fixed effects; individual instructors were not significantly associated with students’ likelihood of passing.

6 This generalization of our results assumes that our results apply to all CUNY students assessed as needing elementary algebra. Note that there were no significant differences between consenters and nonconsenters in measured variables except being underrepresented, but that variable showed no significant relationship with the results in the experiment.
References


Castleman, B.L., & Page, L.C. (2014). *Summer melt: Supporting low-income students through*
the transition to college. Cambridge, MA: Harvard Education Press.


CUNY Office of Institutional Research (2015a). Graduation rates of students with remedial needs.


Should Students Assessed as

analytics-2.pdf


Table 1

*Means [95% CIs]* of Characteristics of Participants, Noncompliers, and Nonconsenters Who Took Algebra in Fall 2013

<table>
<thead>
<tr>
<th>Student Characteristic</th>
<th>Participants</th>
<th>Noncompliers</th>
<th>Nonconsenters</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age missing</td>
<td>.00 [0.00, 0.00]</td>
<td>.18 [0.12, 0.23]</td>
<td>.00 [0.00, 0.00]</td>
</tr>
<tr>
<td>Compass z-score (algebra)</td>
<td>-.00 [-0.07, 0.07]</td>
<td>.01 [-0.08, 0.10]</td>
<td>-.01 [-0.07, 0.05]</td>
</tr>
<tr>
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<td>.08 [0.06, 0.10]</td>
<td>.66 [0.59, 0.73]</td>
<td>.20 [0.17, 0.23]</td>
</tr>
<tr>
<td>Days to consent</td>
<td>77.10 [75.52, 78.67]</td>
<td>69.32 [65.24, 73.41]*</td>
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</tr>
<tr>
<td>First language (English)</td>
<td>.56 [0.52, 0.60]</td>
<td>.57 [0.52, 0.61]</td>
<td>.53 [0.50, 0.56]</td>
</tr>
<tr>
<td>First language missing</td>
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<td>.58 [0.51, 0.65]</td>
<td>.00 [0.00, 0.00]</td>
</tr>
<tr>
<td>Gender (female)</td>
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<td>.57 [0.50, 0.64]</td>
<td>.57 [0.54, 0.60]</td>
</tr>
<tr>
<td>Gender missing</td>
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<td>.05 [0.02, 0.09]</td>
<td>.00 [0.00, 0.00]</td>
</tr>
<tr>
<td>High school GPA z-score</td>
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<td>.35 [0.28, 0.42]</td>
<td>.16 [0.14, 0.18]</td>
</tr>
<tr>
<td>Race (underrepresented)</td>
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<td>.84 [0.80, 0.87]</td>
<td>.76 [0.73, 0.78]**</td>
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<td>.61 [0.54, 0.68]</td>
<td>.00 [0.00, 0.00]</td>
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<tr>
<td>N</td>
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<td>190</td>
<td>1179</td>
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</table>

* Participants and noncompliers different, *p* < .05.

** Participants and nonconsenters different, *p* < .05.
Table 2

*Means [95% CIs] of Characteristics of Participants*

<table>
<thead>
<tr>
<th>Student Characteristic</th>
<th>EA</th>
<th>EA-WS</th>
<th>Stat-WS</th>
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</thead>
<tbody>
<tr>
<td>Age (years)</td>
<td>21.16[20.41,21.92]</td>
<td>21.55[20.73,22.38]</td>
<td>20.45[20.00,20.91]</td>
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<td>Days to consent</td>
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<td>First language (English)</td>
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<td>.56[.50,.61]</td>
</tr>
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<td>.07[.04,.10]</td>
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<td>.55[.49,.61]</td>
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<tr>
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<td>297</td>
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Table 3

*Attrition Following Random Assignment and Withdrawal During the Semester*

<table>
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<th>Group</th>
<th>Attrition*</th>
<th>Withdrawal**</th>
</tr>
</thead>
<tbody>
<tr>
<td>EA-WS</td>
<td>27.48[22.50,32.45]</td>
<td>16.67[11.73,21.61]</td>
</tr>
</tbody>
</table>

* F(2,904)=6.23, p=.002

** F(2,702)=0.14, p=.870
Table 4

*Estimates of Treatment Effects on Passing*

<table>
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<tr>
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<th>With Covariates</th>
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<tr>
<td></td>
<td>ITT</td>
<td>TOC</td>
<td>ITT</td>
<td>TOC</td>
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<tr>
<td>Group Means</td>
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<td></td>
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<td>.35</td>
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<td>.33</td>
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<td>Stat-WS</td>
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<td>Treatment effects</td>
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<td>Stat-WS vs. EA</td>
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<td>[.06,.25]</td>
<td>[.04,.18]</td>
<td>[.05,.22]</td>
<td></td>
</tr>
</tbody>
</table>

*Note.* For covariates see text. ITT = Intent to treat. TOC = Treatment on compliers. 95% CIs in brackets.

* p < .01

**p < .001
Table 5

*ITT Estimates of Treatment Effects on Total Credits Accumulated During Experiment’s Semester and the Year Following*

<table>
<thead>
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<th>Total Credits</th>
<th>Including Statistics</th>
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<td>Covariates</td>
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<td>Group Means</td>
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<td>EA</td>
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<td>EA-WS</td>
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<td>Stat-WS</td>
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Treatment effects

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<td>Covariates</td>
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<td>[-3.57,0.83]</td>
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<tr>
<td>Stat-WS vs. EA</td>
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<td>4.40***</td>
</tr>
<tr>
<td></td>
<td>[2.32,7.03]</td>
<td>[2.21,6.59]</td>
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<tr>
<td>Stat-WS vs. EA</td>
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<td></td>
<td>[3.72,8.37]</td>
<td>[3.22,7.55]</td>
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</table>

*Note. For covariates see text. 95% CIs in brackets. N=907.*

*p<.05, **p<.01, ***p < .001*
Table 6

*Logistic Regression Model Predicting Participants Passing (N=717)*

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean Marginal Effect [95% CIs]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Treatment Status (ref: Group EA)</td>
<td></td>
</tr>
<tr>
<td>Group EA-WS</td>
<td>.07[-.01,.16]</td>
</tr>
<tr>
<td>Group Stat-WS</td>
<td>.17[.08,.25]**</td>
</tr>
<tr>
<td>College (ref: College B)</td>
<td></td>
</tr>
<tr>
<td>College A</td>
<td>.02[-.08,.11]</td>
</tr>
<tr>
<td>College C</td>
<td>.015[-.07,.10]</td>
</tr>
<tr>
<td>Age (years)</td>
<td>.00[-.01,.01]</td>
</tr>
<tr>
<td>Compass z-score (algebra)</td>
<td>.13[.09,.16]**</td>
</tr>
<tr>
<td>Compass score missing</td>
<td>.02[-.10,.15]</td>
</tr>
<tr>
<td>Days to consent</td>
<td>-.00[-.00,.00]</td>
</tr>
<tr>
<td>First language (English)</td>
<td>-.09[.16,-.02]*</td>
</tr>
<tr>
<td>Gender (female)</td>
<td>.01[-.06,.08]</td>
</tr>
<tr>
<td>High school GPA z-score</td>
<td>.08[.04,.11]**</td>
</tr>
<tr>
<td>Instructor experience (years)</td>
<td>.00[-.01,.01]</td>
</tr>
<tr>
<td>Instructor has taught statistics</td>
<td>-.02[-.12,.07]</td>
</tr>
<tr>
<td>Instructor has tenure</td>
<td>.03[-.06,.11]</td>
</tr>
<tr>
<td>Race (underrepresented)</td>
<td>-.07[-.17,.04]</td>
</tr>
</tbody>
</table>

* * p<.05. ** p<.001.
Table 7

*Participant Mathematics Attitudes*

<table>
<thead>
<tr>
<th>Group</th>
<th>Measure</th>
<th>Ability</th>
<th>Interest</th>
<th>Growth</th>
<th>Utility</th>
</tr>
</thead>
<tbody>
<tr>
<td>EA</td>
<td>Pre-Survey M</td>
<td>18.49</td>
<td>14.10</td>
<td>15.12</td>
<td>14.26</td>
</tr>
<tr>
<td></td>
<td>[95% CI]</td>
<td>[17.27,19.71]</td>
<td>[13.13,15.08]</td>
<td>[14.24,16.01]</td>
<td>[13.45,15.08]</td>
</tr>
<tr>
<td></td>
<td>Post-Survey M</td>
<td>19.08</td>
<td>15.46</td>
<td>14.75</td>
<td>14.56</td>
</tr>
<tr>
<td></td>
<td>[95% CI]</td>
<td>[17.84,20.31]</td>
<td>[14.46,16.47]</td>
<td>[13.69,15.80]</td>
<td>[13.70,15.41]</td>
</tr>
<tr>
<td></td>
<td>t(df)</td>
<td>0.93(105)</td>
<td>2.82(105)***</td>
<td>-0.74(105)</td>
<td>0.66(105)</td>
</tr>
<tr>
<td>EA-WS</td>
<td>Pre-Survey M</td>
<td>17.52</td>
<td>13.57</td>
<td>15.35</td>
<td>14.33</td>
</tr>
<tr>
<td></td>
<td>[95% CI]</td>
<td>[16.38,18.66]</td>
<td>[12.57,14.56]</td>
<td>[14.62,16.08]</td>
<td>[13.49,15.17]</td>
</tr>
<tr>
<td></td>
<td>Post-Survey M</td>
<td>17.26</td>
<td>15.15</td>
<td>15.21</td>
<td>14.34</td>
</tr>
<tr>
<td></td>
<td>[95% CI]</td>
<td>[16.11,18.42]</td>
<td>[14.23,16.07]</td>
<td>[14.24,16.17]</td>
<td>[13.45,15.23]</td>
</tr>
<tr>
<td></td>
<td>t(df)</td>
<td>-0.47(105)</td>
<td>3.14(105)***</td>
<td>-0.27(105)</td>
<td>0.019</td>
</tr>
<tr>
<td>Stat-WS</td>
<td>Pre-Survey M</td>
<td>18.38</td>
<td>13.44</td>
<td>14.87</td>
<td>13.33</td>
</tr>
<tr>
<td></td>
<td>[95% CI]</td>
<td>[17.39,19.37]</td>
<td>[12.56,14.32]</td>
<td>[14.08,15.67]</td>
<td>[12.58,14.09]</td>
</tr>
<tr>
<td></td>
<td>Post-Survey M</td>
<td>18.56</td>
<td>15.29</td>
<td>15.89</td>
<td>14.32</td>
</tr>
<tr>
<td></td>
<td>[95% CI]</td>
<td>[17.48,19.65]</td>
<td>[14.42,16.17]</td>
<td>[14.98,16.80]</td>
<td>[13.49,15.15]</td>
</tr>
<tr>
<td></td>
<td>t(df)</td>
<td>0.37(125)</td>
<td>4.10(125)***</td>
<td>2.14(125)*</td>
<td>2.42(125)**</td>
</tr>
</tbody>
</table>

*p<.05.  **p<.01.  ***p<.005
Figure 1. Flow of target students through recruitment, random assignment, and treatment (* = includes those who took another CUNY mathematics/quantitative course, stayed at CUNY but did not take any mathematics/quantitative course, registered at nonCUNY colleges/universities, or did not register anywhere).
Figure 2. Course pass rates. Second-fourth bars show pass rates for experiment’s research sections. First bar shows comparison elementary algebra pass rate at experiment’s three colleges one year prior to experiment (fall 2012). Fifth bar shows pass rate of Stat-WS students whose Compass (placement examination) scores were relatively high ($\geq 43$ on prealgebra and $\geq 19$ on algebra). Sixth bar shows comparison statistics pass rate at experiment’s three colleges one year prior to experiment.
Figure 3. Probability of passing as a function of Compass algebra z-score with covariates. A logistic regression model including a (nonsignificant) interaction term for the relationship between placement test score and treatment group was used. The nonsignificant interaction term indicates that the slopes of the three functions are not significantly different.
Figure 4. Quantitative-course status of participants one year after experiment’s end.
Appendix A
Student Recruitment Flyer
[College A]
CUNY Math Study Fall 2013

YOU HAVE A CHANCE TO BE A PART OF AN IMPORTANT MATHEMATICS EDUCATION RESEARCH STUDY.

- Are you a new freshman student, starting [College A] in the fall 2013 semester?
- Are you 18 or older?
- Have you been placed in basic skills Mathematics [XXX]?
- Are you available to take classes during the daytime?
- Are you planning to major in either: Liberal Arts, Accounting, Business Management (not Administration), Computer Information Systems or Network Technology (not Computer Science), Video Arts, Health Information Technology, Communications, Literature, Theater, Criminal Justice, Child Care or Human Services?

If you answered YES to these questions you may be eligible to participate in an important CUNY Research Study.

The purpose of this Research Study is to compare student learning and student satisfaction in a pre-college basic skills math course [XXX] with a basic skills enhanced college-level math course [XXX]. The results of this study may identify an accelerated delivery method for mathematics education.

Benefits include:

- A one-in-three chance to skip remediation in math and go directly to an enhanced college-level mathematics course, [XXX]
- A guaranteed mathematics section during the daytime
- Metro cards valued at $50

If you are interested, SEE AN ADVISOR. When you receive your registration appointment, or if you have already registered, please tell your Advisor that you are interested in participating in the study. Your Advisor will help you sign up.

If you have questions, please feel free to contact the research assistant for the project at [College A], ..., or ....
Appendix B

Student Consent Form

CITY UNIVERSITY OF NEW YORK

[College A]
Department of Mathematics

CONSENT TO PARTICPATE IN A RESEARCH PROJECT

Project Title: Mainstreaming Mathematics Remedial Students

Principal Investigator: [XXX]

Co-Investigator: [XXX]

Faculty Advisor: [XXX]
(Site Manager)

Site where study is to be conducted: [College A]

Introduction/Purpose: You are invited to participate in a research study. The study is conducted under the direction of [XXX]. The purpose of this research study is to compare student learning and student satisfaction in a college-level course [XXX] with a remedial course [XXX]. The results of this study may identify an effective delivery method of mathematics remediation.

Procedures: This study will take place at [College A] in the Fall 2013 semester. Approximately 300 individuals are expected to participate in this study. Each subject will be randomly assigned (“randomly” means by chance), by a computer program, into one of the three groups described below. That is, you will have an equal chance of being placed in either group. You will not be able to choose your professor.

If you are in Group 1, you will be assigned to an elementary algebra course, [XXX], that will meet twice a week…. You will not receive any college credit for successfully completing the course.

If you are in Group 2, you will be assigned to an elementary algebra course, [XXX], that will meet twice a week… and will be asked to take an additional workshop (once a week; 2 hours total). During the workshop, you will work on practice questions and do homework using a computer program with a peer workshop leader (tutor). You will not receive any college credit for successfully completing the course.
If you are in Group 3, you will be assigned to a college-level introductory statistics course, [XXX], and will be asked to take an additional workshop (once a week; 2 hours total). During the workshop, you will work on practice questions and do homework using a computer program with a peer workshop leader (tutor). You will receive [X] credits for successfully completing this course…..

All students (Groups 1, 2, and 3) will be asked to take a paper-and-pencil survey (10-15 minutes) at the end of the semester. The survey will ask about your experience in the course. Your responses to the survey will not affect your grade and will be used for research purposes only.

**Possible Discomforts and Risks:** Your participation in this study may involve placement in a course that may not work as well for you as an alternative might have. While there is no risk of physical discomfort, your placement in a class that you are not yet ready for may result in no credit for the course. If you are bothered as a result of this study, you should contact the Institutional Research Board (a group of people who review the research to protect your rights). Contact Ms. Arita Winter at 646-664-8919 or arita.winter@cuny.edu.

**Benefits:** If you agree to participate in the study, you have a one-third of chance to be assigned to a college-level introductory statistics course, MAT150, which means that you will be able to skip a mathematics remedial course. However, you will need to successfully complete the course to receive credit for the course. If you fail to do so, you will receive an NC (no credit) grade, which will not affect your G.P.A.; however, you will need to take a remedial course [XXX], in which you are originally placed as a result of the assessment test, in a future semester.

Also, the results of this research will add to our knowledge about how to improve remedial education for college students. Future students may benefit from the information that is learned in the study.

**Voluntary Participation:** Your participation in this study is voluntary, and you may decide not to participate without prejudice, penalty, or loss of benefits to which you are otherwise entitled. If you decide to leave the study, please contact the Co-Investigator, [XXX] to inform your decision.

**Financial Considerations:** There are no additional financial costs for participating in the study.

As an incentive to participate in the study, you will receive MTA Metrocards (a total value of $50) regardless of the group you are assigned to. A $40 Metrocard will be given to you at the end of September and a $10 Metrocard will be given at the end of the semester. You will need to remain in the study at these times, respectively, to receive each of the two Metrocards.

**Confidentiality:** The data obtained from you will be collected via written documents which will be transferred to a digital format. The collected data will be accessible to the Principal Investigator, Co-Investigator, Faculty Advisor (Site Manager), and IRB members. The researchers will protect your confidentiality by coding and securely storing the data. The collected data will be stored in a locked cabinet, and encrypted files on a computer. Consent will be kept separate from the data.
The data/results from this study will be used by CUNY to put together reports and/or presentations about mathematics remedial education. These reports may be shared with others, either electronically or in print form.

Each student’s personal information will not be included or mentioned in any reports or presentations.

**Contact Questions/Persons:** If you have any questions about the research now or in the future, you should contact the Co-Investigator, [XXX]. If you have any questions concerning your rights as a participant in this study, you may contact Ms. Arita Winter at 646-664-8919 or arita.winter@cuny.edu.

**Statement of Consent:**

“I have read the above description of this research and I understand it. I have been informed of the risks and benefits involved, and all my questions have been answered to my satisfaction. Furthermore, I have been assured that any future questions that I may have will also be answered by the principal investigator of the research study. I voluntary agree to participate in this study.

By signing this form I have not waived any of my legal rights to which I would otherwise be entitled. I will be given a copy of this statement.”
Appendix C

Power Analysis

A power analysis indicated that to detect a pass rate difference of 32% between the EA and the Stat-WS groups (the usual pass rates were 37% and 69%, respectively) with 95% power would require at least 60 students per group. Given the possibility of significant attrition among the recruited students, and of a lower-than-usual statistics pass rate, and given that we intended to conduct subgroup analyses, we aimed to recruit a total of approximately 900 students.
Appendix D
Faculty Orientation Agenda

Faculty Orientation for Math Remediation Experiment
College A

Agenda

Day 1
- Orientation overview
  • Day 1-2 – overview of the pilot study, the large-scale study, research in general
  • Day 3 – course materials, suggestions and instructions to peer workshop leaders

- Pilot study overview (Fall 2012)
  • Purpose/background
  • Three conditions (one section per condition)
    ➢ Condition 1 – [XXX]
    ➢ Condition 2 – [XXX] and peer workshop
    ➢ Condition 3 – [XXX] and peer workshop
  • Target students
  • Student recruitment procedure (75 students, 25 per condition)
  • Peer workshop leader recruitment procedure
  • During intervention
    ➢ Peer workshop leader will observe all class meetings (Conditions 2 and 3)
    ➢ Instructor and peer workshop leader will meet periodically.
    ➢ [Research personnel] will visit a class meeting once a month.
    ➢ Instructor and [research personnel] will meet once a month (1 hour each).
  • Data collection
    ➢ Attendance
    ➢ Homework completion
    ➢ Quiz scores
    ➢ Midterm/finals scores
    ➢ Final grades
    ➢ Withdrawal/dropouts
    ➢ Survey

- Large-scale study (Fall 2013)
- Three conditions, 4 sections per condition
- 300 students, 100 per condition
- One instructor teaches three sections, one condition each.

### Day 2

- **Research in general**
  - Types of research
    - Correlational
    - Quasi-experimental
    - Experimental
  - Variables
    - Independent variable
    - Dependent variable
    - Confounding variable
  - Validity
    - Internal validity
    - External validity
  - Threats to internal validity

- **Ethical research conduct**
  - IRB
  - Please take CITI training ([https://www.citiprogram.org](https://www.citiprogram.org))
    - Create an account (affiliation “CUNY”)
    - Complete modules for “HSR for Social & Behavioral Faculty, Graduate Students & Postdoctoral Scholars”
    - Transfer your completion report to a Word or pdf document
    - Email your report to [research personnel] by the end of 6/26.

### Day 3

- **Day overview**
  - Go over syllabi and textbooks for [XXX] and [XXX] and discuss how instructors teach similarly and differently.
  - Any topics that need to be emphasized?
  - Suggestions for peer workshop leaders
Appendix E
Sample Elementary Algebra Syllabus

College A
City University of New York
Department of Mathematics

Elementary Algebra  
MAT XXX  
Instructor:  
Telephone:  

Class hours: 
Credits: 0  
Office:  
Email:  

Course Description:  
This course is the lowest level algebra course offered at the college. It includes topics such as arithmetic with integers, algebraic representation, operations with polynomials, solving linear equations, solving systems of two linear equations in two variables, exponents and radicals, factoring and graphing linear equations.

Pre/Co-Requisites:  
Pre-Requisite: [XXX]. Students who score less than 40 on the COMPASS algebra exam are eligible to take [XXX]. Students must also have pre-algebra COMPASS score of at least 35 or have successfully completed [XXX].
**Student Learning Outcomes and Assessment:**

<table>
<thead>
<tr>
<th>Course Student Learning Outcomes</th>
<th>Measurements</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>1) Operations</strong></td>
<td></td>
</tr>
<tr>
<td>a. Radicals. Includes only square roots of nonnegative numbers.</td>
<td></td>
</tr>
<tr>
<td>i. Simplify radical terms (no variable in the radicand).</td>
<td></td>
</tr>
<tr>
<td>ii. Perform addition, subtraction, multiplication and division using like and unlike radical terms and express the result in simplest form.</td>
<td></td>
</tr>
<tr>
<td>b. Scientific Notation</td>
<td></td>
</tr>
<tr>
<td>i. Convert between standard decimal and scientific notation.</td>
<td></td>
</tr>
<tr>
<td>ii. Understand and use scientific notation to compute products and quotients of numbers.</td>
<td></td>
</tr>
<tr>
<td>iii. Understand and use scientific notation to compute sums and differences of numbers.</td>
<td></td>
</tr>
<tr>
<td>c. Exponents.</td>
<td></td>
</tr>
<tr>
<td>Multiply and divide monomial expressions with a common base using the properties of exponents. All exponents are integral.</td>
<td></td>
</tr>
<tr>
<td><strong>2) Variables and Expressions</strong></td>
<td></td>
</tr>
<tr>
<td>a. Translate a quantitative verbal phrase into an algebraic expression.</td>
<td></td>
</tr>
<tr>
<td>b. Add and subtract monomials and polynomials.</td>
<td></td>
</tr>
<tr>
<td>c. Multiplication of a monomial and binomial by any degree polynomial.</td>
<td></td>
</tr>
<tr>
<td>d. Divide a polynomial by a monomial, where the quotient has no remainder.</td>
<td></td>
</tr>
<tr>
<td>e. Factoring</td>
<td></td>
</tr>
<tr>
<td>i. Identify and factor the greatest common factor from an algebraic expression.</td>
<td></td>
</tr>
<tr>
<td>ii. Identify and factor the difference of two perfect squares.</td>
<td></td>
</tr>
<tr>
<td>iii. Factor all trinomials of a single variable, including a leading coefficient other than 1.</td>
<td></td>
</tr>
<tr>
<td>iv. Factor algebraic expressions by grouping with up to 4 terms</td>
<td></td>
</tr>
<tr>
<td>v. Factor algebraic expressions completely where the factorization requires more than one step</td>
<td></td>
</tr>
<tr>
<td><strong>3) Equations and Inequalities</strong></td>
<td></td>
</tr>
<tr>
<td>a. Translate verbal sentences into mathematical equations.</td>
<td></td>
</tr>
<tr>
<td>b. Solve all types of linear equations in one variable.</td>
<td></td>
</tr>
<tr>
<td>c. Systems of Linear Equations (2x2)</td>
<td></td>
</tr>
<tr>
<td>i. Solve systems of two linear equations in two variables algebraically.</td>
<td></td>
</tr>
<tr>
<td>ii. Graph and solve systems of linear equations with rational coefficients in two variables.</td>
<td></td>
</tr>
<tr>
<td>d. Solve literal equations for a given variable.</td>
<td></td>
</tr>
<tr>
<td><strong>Measurements</strong></td>
<td></td>
</tr>
<tr>
<td>Homework, quizzes, online problem assignments, midterm, final exam, MATH CUNY-Wide EXAM</td>
<td></td>
</tr>
</tbody>
</table>
e. Quadratic Equations:
   i. Understand and apply the multiplication property of zero to solve quadratic equations with integral coefficients.
   ii. Solve quadratic equations with no linear term.
   iii. Determine the measure of a third side of a right triangle using the Pythagorean Theorem, given the lengths of any two sides.

f. Linear inequalities in a single variable
   i. Solve linear inequalities in one variable.
   ii. Represent solutions to linear inequalities as a single inequality.
   iii. Represent the solution to a linear inequality in one variable on a number line.

4) **Functions and functional notation.**
   a. Use function notation to compute a single output for simple linear and quadratic relationships.
   b. Use function notation to generate a table of values.

5) **Coordinate Geometry**
   a. Slope and equations of a line
      i. Determine the slope of a line, given the coordinates of two points on the line.
      ii. Write the equation of a line, given its slope and the coordinates of a point on the line.
      iii. Write the equation of a line, given the coordinates of two points on the line.
      iv. Write the equation of a line parallel to the x – or y-axis.
      v. Determine the slope of a line, given its equation in any form.
      vi. Write and transform equations of lines in the following forms
          1. Point-Slope form
          2. Slope Intercept form
          3. \( Ax + By = C \) form
   b. Draw and recognize graphs of lines.

6) **Proportions and percent**
   a. Solve simple verbal problem with two quantities that are proportional.
   b. Solve simple verbal problem involving a single percent and/or a single percent increase/decrease.

**General Education Outcomes and Assessment:**

<table>
<thead>
<tr>
<th>General Education Learning Outcomes</th>
<th>Measurements</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Communication Skills</strong>- Students will be able to write, read, listen and speak critically and effectively.</td>
<td>Homework, quizzes, online problem assignments, midterm, final exam, MATH CUNY-Wide EXAM</td>
</tr>
<tr>
<td><strong>Quantitative Reasoning</strong>- Students will be able to use quantitative skills and the concepts and methods of mathematics to solve problems.</td>
<td>Homework, quizzes, online problem assignments, midterm, final exam, MATH CUNY-Wide EXAM</td>
</tr>
<tr>
<td><strong>Information &amp; Technology Literacy</strong>- Students will be able to collect, evaluate and interpret information and effectively use information technologies.</td>
<td>Homework, quizzes, online problem assignments, midterm, final exam, MATH CUNY-Wide EXAM</td>
</tr>
</tbody>
</table>
Required Text and Readings (One of the three options* is required):


*NOTE: Options 1 and 2 are available through [XXX]. Option 3 is available through the college bookstore.

Math Lab Use: The Math Lab is located in [XXX]. You will need a valid College A student ID to visit the Math Lab. Tutors are available in the Math Lab for free to all College A students. The Math Lab has worksheets with practice problems in stock, as well as computer- and video-based tutoring.

Use of Technology: All students are required to use the WebAssign online courseware system. It contains videos, homework problems, chapter tests and quizzes, step-by-step help, an online version of the textbook, and more. Students can access the online courseware only by buying a new textbook that contains a student access card or by buying a separate access code from the bookstore or the publisher (at www.webassign.net).

Steps to register for WebAssign:

1. Have your access code card ready.
2. Make sure to get the Class Key for your course from your instructor.
3. Go to https://www.webassign.net/v4cgi/selfenroll/classkey.html
4. Enter the Class Key and then click submit. The screen looks like this: This is only an example. Make sure you use the Class Key given to you by your instructor.
5. On the next page, verify the course, section and instructor by choosing “Yes, this is my class,”
6. After verifying your class’ information, you will see two options:
   - “I need to create a WebAssign account.”
   - “I already have a WebAssign account.”
   If you choose “I need to create a WebAssign account,” move to step 7.
If you choose “I already have a WebAssign account” then sign in (institution: College A).
If you don’t remember your password then open a new tab or window and go to https://www.webassign.net/login.html?password=forgot to recover it.
7. Create your own password and username. It can be any username and password that you want. Enter the email address you use regularly (it does not have to be your College A email address). Write this username and password in a safe place.
   Username: ______________
   Password: ______________
From now on, you will get in by going to www.webassign.net and clicking enter your username, the institution (College A) and password in the ACCOUNT LOG IN section.
8. After logging in you may see a notice that includes Grace Period information and payment options. You can “register a code number if you have an Access Code card” or “you can buy an Access Code online via a credit card, debit card or Pay Pal account”. After the Grace Period you will see the payment options and not be able to continue without entering an Access Code.
Evaluation and Requirements of Students:
The final grade in this course will be a passing grade of S, or a failing grade of R. The **Class Grade will be 65% of the total grade and the CUNY EXAM will be 35% of the total grade.** A passing grade for the Midterm exam is **70 or higher.** A passing grade for the Departmental Final exam is **70 or higher.** A passing grade for the CUNY EXAM is **60 or higher.** Students must pass the CUNY EXAM to pass the course, in addition to satisfying a total grade of **74% or better.**

If a student fails the Midterm exam, the student is required to complete the online Intervention Assignments (on WebAssign) with a score of **70 or better.** The Intervention Assignment grade will replace the Midterm grade.

Those students who pass the Departmental Midterm Exam with a 70 or better are exempt from the Intervention Assignment Requirement, but are **strongly** encouraged to do those assignments for practice. Our research has shown that **many more** students who do the Intervention Assignments pass the Departmental Final Exam than those who do not. Thus, it is a good idea for **all** students to do the Intervention Assignments, even if they have passed the midterm. These assignments are an **excellent** way to prepare for the Departmental Midterm and Final Exams.

**Grade Distribution:**

* **Suggested**
  
  - Homework: **20 %**
  - Exams and quizzes: **25 %**
  - Departmental Final: **5 %**

* **Required**
  
  - Midterm: **15 %**
  - CUNY EXAM **35 %**

**College Attendance Policy:**

1. **Absences**
   
   At College A, the maximum number of absences is limited to one more hour than the number of hours a class meets in one week. For this course, you are allowed five hours of absence (not five days). **In the case of excessive absence, the instructor has the option to lower the grade or assign an “R” or “WU” grade.**

2. **Class Attendance**
   
   If you do not attend class at least once in the first three weeks of the course and once in the fourth or fifth weeks, the Office of the Registrar is required to assign a grade of “WU”. Attendance in both regular and remedial courses is mandated by policy of the City University of New York. Instructors are required by New York State law to keep an official record of class attendance.

3. **Lateness**
   
   Classes begin promptly at the times indicated in the Schedule of Classes. Arrival in classes after the scheduled starting time constitutes a lateness. Latecomers may, at the discretion of the instructor, incur an official absence.

**Academic Adjustments for Students with Disabilities:**

Students with disabilities who require reasonable accommodations or academic adjustments for this course must contact the Office of Services for Students with Disabilities. College A is committed to providing equal access to all programs and curricula to all students.

**College A Policy on Plagiarism and Academic Integrity Statement:**

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Students who are unsure how and when to provide documentation are advised to consult with their instructors. The library has guides designed to help students to appropriately identify a cited work. The full policy can be found on College A’s web site. For further information on integrity and behavior, please consult the college bulletin (also available online).
<table>
<thead>
<tr>
<th>Suggested Schedule:</th>
</tr>
</thead>
</table>
| **Week 1** | Chapter 1  The Basics  
| 1.1 Variables, Notation, and Symbols  
| 1.2 Real Numbers  
| 1.3 Addition and Subtraction of Real Numbers  
| 1.4 Multiplication of Real Numbers  
| 1.5 Division of Real Numbers  |
| **Week 2** | 1.6 Properties of Real Numbers  
| 1.7 Subsets of Real Numbers  
| 1.8 Addition and Subtraction of Fractions with Variables  
| Chapter 2  Linear Equations and Inequalities  
| 1.1 Simplifying Expressions  
| 2.2 Addition Property of Equality  |
| **Week 3** | 2.3 Multiplication Property of Equality  
| 2.4 Solving Linear Equations  
| 2.5 Formulas  
| 2.6 Applications  |
| **Week 4** | 2.7 More Applications  
| 2.8 Linear Inequalities  
| Chapter 3  Linear Equations and Inequalities in Two Variables  
| 3.1 Paired Data and Graphing Ordered Pairs  
| 3.2 Solutions to Linear Equations in Two Variables  |
| **Week 5** | 3.3 Graphing Linear Equations in Two Variables  
| 3.4 More on Graphing: Intercepts  
| 3.5 The Slope of a Line  
| 3.6 Finding the Equation of a Line  
| **Functional Notation (Supplemental Material)** |
| **Week 6** | Chapter 4  Systems of Linear Equations  
| 4.1 Solving Linear Equations by Graphing  
| 4.2 The Elimination Method  
| 4.3 The Substitution Method  
| 4.4 Applications  |
| **Week 7** | Review for Midterm Exam  
| **Departmental Midterm Exam:** Signed  
| Numbers, Algebraic Expressions and Equations, Solving and Graphing Linear Equations/Inequalities, Systems of Linear Equations, functional notations  |
| **Week 8** | Chapter 5  Exponents and Polynomials  
| 5.1 Multiplication with Exponents  
| 5.2 Division with Exponents  
| 5.3 Operations with Monomials  
| 5.4 Addition and Subtraction of Polynomials  |
| **Week 9** | 5.5 Multiplication with Polynomials  
| 5.6 Binomial Squares and Other Special Products  
| 5.7 Dividing a Polynomial by a Monomial  
| Chapter 6  Factoring  
| 6.1 The GCF and Factoring by Grouping  |
| **Week 10** | 6.2 Factoring Trinomials  
| 6.3 More Trinomials to Factor  
| 6.4 The Difference of Two Squares  |
| **Week 11** | 6.6 Factoring: A General Review  
| Chapter 8  Square Roots  
| 8.1 Definitions and Common Roots  |
| **Week 12** | Review for Final Exam  |
| **Week 13** | **Department Final Exam**  |
| **Week 14** | 8.2 Properties of Radicals  
| 8.3 Operations with Radicals  
| Review for the MATH CUNY-Wide EXAM  |
| **Week 15** | MATH CUNY-Wide EXAM  |
Appendix F
Sample Introductory Statistics Syllabus

College A
City University of New York
Department of Mathematics

INTRODUCTION TO STATISTICS
MAT XXX
Instructor: Telephone: Office: Email:

Class hours: Credits:

A. Course Description
This course covers the study of basic statistics. It includes measures of central tendency, measures of dispersion, graphs, the chi-square distribution, the normal distribution, sampling distributions, t-tests and correlation.

B. Prerequisites and co-requisites
The student must have passed or have been exempted from MAT [XXX], MAT [XXX] or MAT [XXX]. This course satisfies the mathematics requirement for majors in Accounting, Business Management, Liberal Arts (but not the Science concentration), Office Automation, Medical Records Technology and Community Mental Health Assistant.

C. Required Text and Supplementary Material

Statistical Computer packages are available in the Mathematics Lab (S511) in [XXX].

D. Other Resources
The resources available in the Math Lab (Room [XXX]) include tutors, videotaped lessons, technology (statistics computer programs, graphing calculators and internet access) and additional worksheets.

E. Use of Technology
A scientific calculator is required. The new textbook comes with a free internet account that provides online tutorials, extra practice problems and video recorded lessons. Some MAT [XXX] sections listed in the Schedule of Classes as taught with technology require students to use computers and/or graphing calculators.

F. Evaluation and Requirements of Students
At the beginning of the semester, the instructor will advise the student how the final grade will be determined (based on class work, examinations, quizzes, writing assignments and the final examination). Students are required to attend all scheduled classes.
G. Outline of Topics

<table>
<thead>
<tr>
<th>Class Hours and Page</th>
<th>Text Section</th>
<th>Topic</th>
</tr>
</thead>
<tbody>
<tr>
<td>2 hours Pages 2-26</td>
<td>1.1 – 1.4</td>
<td>Introduction: Overview, Nature of Data, and Uses and abuses of Statistics.</td>
</tr>
<tr>
<td>8 hours Pages 44–135</td>
<td>2.1 – 2.4 &amp; 3.1 – 3.4</td>
<td>Exploring data, Frequency distributions, visualizing data, Measures of Center, Measures of Variation, Measures of relative standing.</td>
</tr>
<tr>
<td>4 hours Pages 136–186</td>
<td>4.1 – 4.6</td>
<td>Probability: Fundamental addition rule, multiplication rule, conditional probability and counting.</td>
</tr>
<tr>
<td>6 hours Pages 196-235</td>
<td>5.1 – 5.4</td>
<td>Probability Distributions; Random variables; binomial distributions; their means, variance and standard deviations.</td>
</tr>
<tr>
<td>8 hours Pages 236–296</td>
<td>6.1 – 6.6</td>
<td>Normal Probability Distributions; Sampling distributions and the Central Limit theorem</td>
</tr>
<tr>
<td>8 hours Pages 314-357</td>
<td>7.1 – 7.4</td>
<td>Confidence Intervals, Estimates and Sample Sizes</td>
</tr>
<tr>
<td>8 hours Pages 378-447</td>
<td>8.1 – 8.6</td>
<td>Steps to test a hypothesis; claims about the mean. P-values and hypothesis tests on proportions</td>
</tr>
<tr>
<td>4 hours Pages 494-528</td>
<td>10.1 – 10.3</td>
<td>Correlation and Regression</td>
</tr>
<tr>
<td>2 hours pages 554-567</td>
<td>11.1 – 11.2</td>
<td>Chi-squared tests of independence and goodness of fit</td>
</tr>
</tbody>
</table>

**College Attendance Policy**

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**Academic Adjustments/Students with Disabilities**

Students with disabilities who require reasonable accommodations or academic adjustments for this course must contact the Office of Services for Students with Disabilities (Room N324;220-8180). College A is committed to providing equal access to all programs and curricula to all students.

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<table>
<thead>
<tr>
<th>Course Student Learning Outcomes (Students will be able to…)</th>
<th>Measurements (means of assessment for student learning outcomes listed in first column)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Students will study basic concepts of descriptive statistics, including graphical representations of data and measures of central tendency, position and dispersion. Students will: knob the difference between a population and a sample. Classify data by type. Design a sampling plan for a statistical study. Construct frequency distributions from data sets. Construct histograms, polygons and ogives from frequency distributions. Construct pie and Pareto charts. Interpret basic charts and graphs Define the vocabulary, terminology and symbols used in statistics. Calculate and interpret key statistics and parameters such as • the mean, the mode, the median, • the standard deviation • quartiles and percentiles • standard (z) scores</td>
<td>1. Quizzes, tests, homework and/or projects</td>
</tr>
<tr>
<td>2. Students will study basic concepts of probability leading to the study of the binomial and normal probability distributions and the Central Limit Theorem. Students will: Identify the sample space of a probability experiment. Find classical and experimental probabilities, and explain how the two are related using the Law of Large Numbers. Use the Multiplication and Addition Rules for finding probabilities. Find permutations and combinations. Construct and graph discrete probability distributions. Find the mean and standard deviation for discrete probability distributions and for binomial probabilities. Find binomial probabilities using the formula and a table and/or technology. Understand the properties of the normal distribution. Use the standard normal table and/or technology to find probabilities. Use the standard normal table and/or technology to find data values. Understand and use the Central Limit Theorem.</td>
<td>2. Quizzes, tests, homework and/or projects</td>
</tr>
</tbody>
</table>
3. Students will be able to construct simple statistical studies and hypothesis tests using Normal distributions as well as with other distributions such as the t and the chi-squared distribution.

Students will:
- Construct confidence intervals for means (large samples).
- Construct confidence intervals for means (small samples).
- Construct confidence intervals for population proportions.
- Perform hypothesis tests for means (large samples).
- Perform hypothesis tests for means (small samples).
- Interpret the results of hypothesis tests and confidence intervals.
- Find the linear correlation coefficient, using software if possible.
- Test the linear correlation coefficient for significance.
- Find the equation of a regression line, using software if possible.
- Predict y values using regression equations.
- Interpret a positive, negative or close to zero correlation.
- Perform Chi Square Goodness-of-Fit tests.

<table>
<thead>
<tr>
<th>General Education Learning Outcomes</th>
<th>Measurements (means of assessment for general education goals listed in first column)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Communication Skills- Students will be able to write, read, listen and speak critically and effectively.</td>
<td></td>
</tr>
<tr>
<td>Quantitative Reasoning- Students will be able to use quantitative skills and the concepts and methods of mathematics to solve problems.</td>
<td>Quizzes, tests, homework and/or projects</td>
</tr>
<tr>
<td>Scientific Reasoning- Students will be able to apply the concepts and methods of the natural sciences.</td>
<td></td>
</tr>
<tr>
<td>Social and Behavioral Sciences- Students will be able to apply the concepts and methods of the social sciences.</td>
<td></td>
</tr>
<tr>
<td>Arts &amp; Humanities- Students will be able to develop knowledge and understanding of the arts and literature through critiques of works of art, music, theatre or literature.</td>
<td></td>
</tr>
<tr>
<td>Information &amp; Technology Literacy- Students will be able to collect, evaluate and interpret information and effectively use information technologies.</td>
<td>Quizzes, tests, homework and/or projects</td>
</tr>
<tr>
<td>Values- Students will be able to make informed choices based on an understanding of personal values, human diversity, multicultural awareness and social responsibility.</td>
<td></td>
</tr>
</tbody>
</table>
Appendix G

Means [95% CIs] of Number of CUNY’s Nine General Education Course Categories

Satisfied by All 907 Randomly Assigned Students

Through One Calendar Year After the End of Experiment

<table>
<thead>
<tr>
<th>General Education</th>
<th>EA</th>
<th>EA-WS</th>
<th>Stat-WS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Category</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Quantitative</td>
<td>.22[.17, .27]*</td>
<td>.21[.17, .26]*</td>
<td>.48[.42, .54]</td>
</tr>
<tr>
<td>Category</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Two Other STEM</td>
<td>.40[.33, .48]</td>
<td>.44[.37, .52]</td>
<td>.33[.27, .40]</td>
</tr>
<tr>
<td>Categories Combined</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Six nonSTEM</td>
<td>2.19[1.96, 2.42]</td>
<td>2.00[1.78, 2.22]</td>
<td>1.67[1.45, 1.89]</td>
</tr>
</tbody>
</table>

* Comparison with Stat-WS p<.001.
Appendix H

A nonlinear (quadratic) model was also used to examine the relationship between passing and treatment group:

\[
\ln \left( \frac{\hat{p}}{1 - \hat{p}} \right) = \delta + \beta_1 \times \text{STATS}_i + \beta_2 \times \text{EAWORK}_i + \beta_3 \times (\text{MATH}_i \times \text{STATS}_i) + \beta_4 \times (\text{MATH}_i \times \text{EAWORK}_i) + \beta_5 \times (\text{MATH}_i)^2 + bX_i + \epsilon_i .
\]

Both the linear and the nonlinear forms are significant. The following figure is based on the nonlinear form. As in Figure 3 (which is based on the linear form), Group Stat-WS consistently has the highest pass rate and Group EA the lowest, and the slopes of the functions for the three treatment groups are not significantly different. The major difference between the graphs based on the linear and nonlinear models is that in the nonlinear form passing reaches an asymptote for each group at a Compass Z-score of approximately 1.0, but in the linear form the functions do not appear to reach an asymptote.
Appendix I

Mixed-Effects Logit Regression Model

To test further instructors’ impact on course outcomes, we used a mixed-effects logit regression model with instructor as the random effect. The results are shown in the table below. Instructor assignment affected students’ probability of passing. However, there was still an effect of treatment group, again indicating that, across classrooms and instructors, Stat-WS students were more likely to pass. A log-likelihood test comparing a standard logistic regression with the mixed-effects model showed the latter to fit the model significantly better, $\chi^2(1)=5.33, p=.011$.

<table>
<thead>
<tr>
<th></th>
<th>Base Model Odds Ratios and Standard Errors$^a$</th>
<th>Random Effects Model Odds Ratios and Standard Errors$^a$</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Treatment (Ref. Group EA)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Group EA-WS</td>
<td>1.45 (.29)</td>
<td>1.52 (.31)*</td>
</tr>
<tr>
<td>Group Stat-WS</td>
<td>2.10 (.42)**</td>
<td>2.14 (.43)**</td>
</tr>
<tr>
<td><strong>College (Ref. College A)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>College B</td>
<td>1.08 (.22)</td>
<td>1.12 (.36)</td>
</tr>
<tr>
<td>College C</td>
<td>1.05 (.24)</td>
<td>1.07 (.37)</td>
</tr>
<tr>
<td><strong>Demographics</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td>1.01 (.02)</td>
<td>1.01 (.02)</td>
</tr>
<tr>
<td>Under-represented Race</td>
<td>0.71 (.18)</td>
<td>0.68 (.17)</td>
</tr>
<tr>
<td>Female</td>
<td>1.10 (.18)</td>
<td>1.07 (.18)</td>
</tr>
<tr>
<td>Native English Speaker</td>
<td>0.70 (.12)*</td>
<td>0.68 (.11)*</td>
</tr>
<tr>
<td><strong>Academic Preparation</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>HS GPA (z-score)</td>
<td>1.07 (.02)**</td>
<td>1.07 (.02)**</td>
</tr>
<tr>
<td>HS GPA missing</td>
<td>1.06 (.20)</td>
<td>1.06 (.20)</td>
</tr>
<tr>
<td>Compass z-score (algebra)</td>
<td>1.86 (.17)**</td>
<td>1.84 (.17)**</td>
</tr>
<tr>
<td>Compass score missing</td>
<td>1.12 (.33)</td>
<td>1.18 (.35)</td>
</tr>
<tr>
<td><strong>Instructor Characteristics</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Tenured</td>
<td>1.13 (.23)</td>
<td>1.10 (.35)</td>
</tr>
<tr>
<td>Has taught statistics</td>
<td>0.88 (.20)</td>
<td>0.86 (.30)</td>
</tr>
<tr>
<td>Years of Experience</td>
<td>1.00 (.01)</td>
<td>1.00 (.02)</td>
</tr>
<tr>
<td><strong>Random Effect Parameter</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Instructor ID</td>
<td>--</td>
<td>0.11 (.08)$^b$</td>
</tr>
</tbody>
</table>

$^a$ The multi-level model fits the data statistically significantly better than the base model: $\chi^2(1)=5.33, p=.011$

$^b$ This random effects parameter estimate is not reported as an odds ratio but as a coefficient.