Carnegie Foundation for the Advancement of Teaching

Community College Pathways' Program Success:

Assessing the First Two Years' Effectiveness of Statway®

November 2014
Hiroyuki Yamada
Carnegie Foundation for the Advancement of Teaching
Stanford, CA

This program of work is supported by Carnegie Corporation of New York, The Bill & Melinda Gates Foundation, The William and Flora Hewlett Foundation, The Kresge Foundation, and Lumina Foundation in cooperation with the Carnegie Foundation for the Advancement of Teaching.

COMMUNITY COLLEGE PATHWAYS
TECHNICAL REPORT

ABSTRACT

Statway® is one of the Community College Pathways initiatives developed by the Carnegie Foundation for the Advancement of Teaching to promote students' progress beginning in developmental math to and through college math credit. Early descriptive results suggested that the Statway program has tripled the success rate for students in half the time to achieve college math credit. This study presents a more rigorous causal analysis of hypothesized program effects. We used a multilevel approach with propensity score matching to evaluate the effectiveness of Statway. Propensity score matching results are consistent with earlier descriptive findings. They replicate across two different cohorts and hold up for varying genders, race/ethnicity groups, and math placement levels. Directions for future work are also suggested.

Community College Pathways' Program Success: Assessing the First Two Years' Effectiveness of Statway®

Community colleges are intended to provide educational opportunities that prepare citizens to lead productive economic lives and contribute as members of society. Every year, however, the hopes and dreams of hundreds of thousands of students are dashed, and their access to economically successful, self-sustaining lives is denied. Approximately 60 percent of incoming students are referred to at least one developmental math course, of which 80 percent will not earn college-level math credit even after three years (Bailey, Jeong, & Cho, 2010). These students lack command of the math that matters for living in an increasingly quantitative age and becoming critically engaged citizens. Without achieving college math credit, they cannot transfer into four-year degree programs or qualify for entry into preparation programs in a wide range of occupational-technical specialties. Without a doubt, this is one of the greatest social equity problems of our time (Cullinane & Treisman, 2010).

To tackle this problem, the Community College Pathways (CCP) was developed and implemented through a Networked Improvement Communities (NICs) structure involving faculty members, researchers, designers, and content experts (Bryk, Gomez, & Grunow, 2011; Dolle, Gomez, Russell, & Bryk, 2013). NICs are scientific learning communities distinguished by four essential characteristics, which are (a) focused on a well specified common aim, (b) guided by a deep understanding of the problem and the system that produces it, (c) disciplined by the rigor of improvement science, and (d) networked to accelerate the development, testing, and refinement of interventions and their effective integration into varied educational contexts. The CCP consists of two different mathematics pathways, Statway® and Quantway®. Statway is a one-year pathway focused on statistics, data analysis, and causal reasoning that combines college-level statistics with developmental math; Quantway focuses on quantitative reasoning – a general education mathematics requirement in many colleges. Both pathways seek to accelerate students' progress through developmental math by allowing them to earn college math credit within a single academic year. (For more details about the Pathways, see Strother, Van Campen, & Grunow, 2013; Van Campen, Sowers, & Strother, 2013). The current report focuses on Statway results from its first two years of implementation.[1]

Statway is designed to target students who are placed two or more levels below college-level math and serve students planning to transfer and continue further studies in humanities or social sciences. To promote their ambitious learning goals, the Statway instructional system employs three research-based principles:

1. Productive struggle: students are more likely to retain what they learn when they expend effort solving problems that are within reach and grappling with key mathematical ideas that are comprehensible but not yet well-formed. Thus, each new concept is introduced with a rich problem that engages students' thinking and encourages this struggle to understand (Hiebert & Grouws, 2007; Schmidt & Bjork, 1992).

[1] The analyses of Quantway success are underway.

2. Explicit connections to concepts: mathematics instruction sometimes focuses on procedural competence at the cost of advancing real conceptual understanding. However, research suggests making explicit connections between mathematical or statistical facts, ideas, and procedures can improve both conceptual and procedural understanding (Boaler, 1998; Hiebert & Grouws, 2007).

3. Deliberate practice: classroom and homework tasks are designed to overcome gaps in understanding, apply what is learned, and deepen facility with key concepts (Ericsson, 2008; Ericsson, Krampe, & Tescher-Römer, 1993). Deliberate practice eschews rote repetition for carefully sequenced problems developed to guide students toward deeper understanding of core concepts (Pashler, Rohrer, Cepeda, & Carpenter, 2007).

Early findings from Year 1 (2011-2012) indicated Statway's success (Strother et al., 2013): Fifty-one percent of students successfully completed the full-year pathway, thereby earning college math credit (with a grade of C or higher). In previous years, only 15 percent of developmental math students achieved a similar level of success within two years of college enrollment. Data from Year 2 (2012-2013) established success rates comparable to those of Year 1 (Van Campen et al., 2013). These findings suggest that Statway tripled the success in half the time.

Statway appears to have achieved extraordinary results. However, some may argue that this is merely the result of selection bias, where certain kinds of students may have been more likely to enroll in Statway, leading to more positive outcomes than there otherwise would have been. To address this issue, the main objective of the current study was to formulate a more rigorous causal test to evaluate the Statway's effectiveness. We used a propensity score matching technique to statistically reduce selection bias and accordingly increase the validity of causal inference (Rosenbaum & Rubin, 1983). Given the nature of our data (i.e., students nested within colleges), we employed a hierarchical linear modeling (HLM) approach (Raudenbush & Bryk, 2002) to obtain propensity scores (Hong & Raudenbush, 2005, 2006). We then separately examined data from Year 1 and Year 2.

A second objective was to track the academic outcomes of students one year after their enrollment in Statway. For this purpose, we compared college-level course credit accumulation between Statway and non-Statway matched groups in the subsequent year.[2] This comparative analysis was intended to determine whether Statway students continue to demonstrate success even after their Statway experience.

[2] This follow-up performance was examined only for Year 1; data from Year 2 were not available in this study.

METHOD

Participants

The CCP first launched during the 2011-2012 academic year. The first cohort of students began Statway in the fall of 2011. This initial cohort of students spanned 19 community colleges across five states. In total, 50 faculty members taught 55 sections of Statway with 1133 students enrolled (Strother et al., 2013). The second cohort included a total of 1553 students enrolled in 77 sections of Statway taught by 67 faculty members. Of the 19 community colleges that participated in Statway, all but one offered Statway in both Year 1 and Year 2 (Van Campen et al., 2013).

Table 1 summarizes the demographic characteristics of Statway students. The vast majority of students placed at least two levels below a college-level math course, and almost half were also required to take at least one developmental reading course. Approximately 60 percent of the students were female, and less than one-third were raised in families where the mother held a two- or four-year college degree. Well over half of the students were minorities.

Data Collection

Institutional researchers from participating colleges provided background data on student characteristics, course enrollment and performance. For Year 1, we excluded two community colleges from the analyses. One college discontinued the program partway through the year because its district mandated an alternative developmental math program. The second college implemented Statway in a non-standard way. Consequently, the Year 1 analytic sample consisted of 928 Statway students from 17 community colleges. For Year 2, we excluded four community colleges: two that implemented Statway in a non-standard way and two that failed to provide the institutional data necessary for propensity score matching. In sum, institutional data were available for 771 Statway students from 15 community colleges. All 15 of these colleges also offered Statway in Year 1.

Study Design

Figure 1 delineates the study design using Year 1 as an exemplar. The first objective in this study was to identify a group of students most comparable with Statway students. Defining an appropriate comparison group in this instance was a little more complex than might normally be the case. Statway is designed as an intensive course intended to fulfill requirements for both developmental math and college-level math within one year of continuous enrollment. Students starting two or more levels behind college-level math typically cannot accomplish this in one year if they follow a traditional program of study. They would need to be enrolled for one and a half to two years to meet the same benchmark. This led us to draw a comparison group consisting of students who began taking their developmental math course one year before their Statway counterparts and then compare both groups' outcomes at the end of the Statway year. Thus, comparison students had two years to achieve the same outcomes that Statway students accomplished in one year. For instance, the comparison group for students who began Statway in fall 2011 consisted of students who began developmental math in fall

2010. These two groups were then compared at the end of the spring 2012. Both groups were also followed for an additional year to examine subsequent course taking and credit accumulation. The same strategy was used to form a comparison group for the second cohort of students beginning Statway in fall 2012.

To obtain propensity scores, we formulated a two-level model with a total of 44 student-level covariates including student background characteristics, course enrollment, and performance during the two years prior to fall 2010/2011 for the Year 1 cohort and during the two years prior to fall 2011/2012 for the Year 2 cohort. Tables 2 and 3 present all of the covariates used and their descriptive statistics for Year 1 and Year 2, respectively. For some variables, students' information is recorded as "unknown," and not all colleges kept data on all variables used in the propensity score matching. For instance, there is a substantial number of unknown records for student placement levels, indicating that data are simply missing or students did not take a placement test. Missing GPAs correspond to students who did not take college-level courses or received grades that do not have an effect on their GPAs (i.e., W [Withdrawals] and I [Incompletes]). Accordingly, we assigned a code of -1 to students without GPA in each GPA variable. To factor these "missing" records in the propensity model, we formulated a dummy variable for each GPA and coded missing GPAs as 1, otherwise 0.

In general, Statway students in Year 1 were more likely to be drawn from a second year or older cohort (i.e., not a first-year student cohort), a somewhat different race/ethnicity composition (notably less Hispanic students), and those placed two levels below college math. They were also much older and took more courses overall in the last two years prior to the Statway start term (except for college math courses). Year 2 included more full-time students and those who took less developmental non-math courses.

We conducted propensity score matching separately for each college by applying a nearest neighbor matching algorithm (Rosenbaum & Rubin, 1985). This algorithm was appropriate for our study because we wanted to retain all Statway students and had a large pool of non-Statway students available for creating matches. We attempted to find up to five matches per Statway student (5:1 ratio matching) to maximize the best matches from the non-Statway student group while still maintaining precision (Ming & Rosenbaum, 2000). We also specified a caliper distance of up to 0.2 to reduce the risk of bad nearest neighbor matches based on recommendations in the literature (Austin, 2011; Rosenbaum & Rubin, 1985).

Next, as portrayed in the middle panel of Figure 1, we estimated the effectiveness of Statway (i.e., success rate difference between the two groups) using an HLM on the matched student groups. Success was defined as a grade of C or higher as determined by classroom instructors.[3] We ran three-level HLM analyses and estimated effects separately for Years 1 and 2. We used faculty as the second level and assigned the faculty ID of the Statway students to their matched comparisons for purposes of the analysis. Student and college were used as levels 1 and 3, respectively. Finally, we compared college-level course performance between the two groups in the subsequent year (the subsequent year was

[3] A grade of C- or higher was used for six colleges that employ a +/– grading system to define college math success.

defined as three consecutive terms, including summer, immediately after spring 2012), as depicted in the right panel of Figure 1. We defined student performance as accumulated units earned with a grade of C or higher.[4] We used HLM 7 (Raudenbush, Bryk, Cheong, Congdon, & du Toit, 2011) for all of the HLM analyses.

[4] A grade of C- or higher was used for six colleges that employ a +/– grading system to define college-level units earned.

RESULTS

Propensity Score Matching

To obtain propensity scores, we formulated a two-level Bernoulli model and estimated its model parameters using maximum likelihood via adaptive Gaussian quadrature. ϕ_{ij} is the probability of student *i* enrolling in Statway in college *j*. Accordingly, η_{ij} is the log-odds of this incident and formally expressed as:

Level-1 Model (Student)

$$\text{Prob}(SW_{ij}=1|\beta_j) = \phi_{ij}$$

$$\log[\phi_{ij}/(1 - \phi_{ij})] = \eta_{ij}$$

$$\eta_{ij} = \beta_{0j} + \beta_{1j}*(COV1_{ij}) + \ldots + \beta_{44j}*(COV44_{ij})$$

Level-2 Model (College)

$$\beta_{0j} = \gamma_{00} + u_{0j},$$

$$\beta_{1j} = \gamma_{10},$$

$$\ldots,$$

$$\beta_{43} = \gamma_{430,}$$

$$\beta_{44j} = \gamma_{440} + u_{44j}$$

where *SW* is a dummy variable indicating whether a given student was enrolled in Statway (coded as 1) or not (coded as 0), *COV* is a covariate, and *i* and *j* denote student and college, respectively. We estimated one random slope, β_{44j}, for a dummy variable indicating a math placement two levels below the college math level to account for some observed heterogeneity among colleges in this relationship**.** Using the matching procedure described above, we identified a total of 4549 comparison students matched to 928 Statway students for Year 1. Using the same matching procedure, we identified a total of 3583 comparison students matched to 771 Statway students for Year 2.[5] Tables 4 and 5 present the balance in propensity score for those students by college for Year 1 and Year 2, respectively. For both cohorts, there were no significant differences in mean propensity score between the Statway and matched students in any of the colleges. Also, Tables 2 and 3 show the descriptive statistics after matching for Year 1 and Year 2, respectively.

[5] As did in Year 1, we estimated one random slope for a math placement two levels below college. However, derived propensity scores were more varied than those from the fixed slope HLM model. Hence, we decided to use propensity scores from the fixed slope model for matching.

Statway Effectiveness

To estimate differences in success rate, we formulated a three-level Bernoulli model[6] and estimated its model parameters using maximum likelihood via adaptive Gaussian quadrature. ϕ_{ijk} represents the probability that student *i* within faculty member *j*'s class in college *k* successfully achieves college math credit. Correspondingly, η_{ijk} is the corresponding log-odds of this outcome and formally expressed as:

Level-1 Model (Student)

$$\text{Prob}(CMA_{ijk}=1|\pi_{jk}) = \phi_{ijk}$$

$$\log[\phi_{ijk}/(1 - \phi_{ijk})] = \eta_{ijk}$$

$$\eta_{ijk} = \pi_{0jk} + \pi_{1jk}*(PS_{ijk}) + \pi_{2jk}*(SW_{ijk})$$

Level-2 Model (Faculty)

$$\pi_{0jk} = \beta_{00k} + r_{0jk}$$

$$\pi_{1jk} = \beta_{10k}$$

$$\pi_{2jk} = \beta_{20k}$$

Level-3 Model (College)

$$\beta_{00k} = \gamma_{000} + u_{00k}$$

$$\beta_{10k} = \gamma_{100}$$

$$\beta_{20k} = \gamma_{200}$$

where *CMA* and *PS* represent college math achievement (1 for successfully completed and 0 for not successfully completed) and a propensity score for additional adjustment. The key predictor of interest, *SW*, is a dummy variable indicating whether the student was enrolled in Statway (coded as 1) or one of the matched comparisons (coded as 0).

The results displayed in Table 6 indicate that on average, Statway students demonstrated significantly higher odds of success, 5.31, in college-level mathematics than the comparison students. This translated into the estimated probabilities of success of 54.43 percent for the Statway group and 18.36 percent for the comparison group. Additionally, we found variation among colleges in student success (Variance = 0.239). Figure 2 shows that all but one college demonstrated greater success in Statway. Most colleges clustered around a line representing "triple the success rate", i.e., Statway students were three times more likely to succeed than their matched students. This is represented by the dotted line in Figure 2.

---

[6] We also ran a four-level model where level 1 is student, level 2 is matched student cluster, level 3 is faculty, and level 4 is college and obtained similar results for both Year 1 and Year 2.

The HLM results for Year 2 are displayed in Table 7. Consistent with Year 1 results, Statway students demonstrated significantly higher odds of success in college-level mathematics, 7.40, as compared to the matched students (55.26 percent vs. 14.30 percent as estimated probabilities of success). The Statway effect on student success also varied across colleges (Variance = 0.342). Again, as portrayed in Figure 3, all but one college clustered around the "triple the success rate" line.

To estimate differences in college credits earned with a grade of C or higher in the subsequent year, we formulated a three-level Poisson model[7] and estimated its model parameters using penalized quasi-likelihood estimation.[8] λ_{ijk} represents the event rate that student *i* within faculty member *j*'s class in college *k* successfully earns college credits in the following year. Thus, η_{ijk} is the corresponding log of this event and formally expressed as:

Level-1 Model (Student)

$$E(CCE_{ijk} | \pi_{jk}) = \lambda_{ijk}$$

$$\log[\lambda_{ijk}] = \eta_{ijk}$$

$$\eta_{ijk} = \pi_{0jk} + \pi_{1jk}*(PS_{ijk}) + \pi_{2jk}*(SW_{ijk})$$

Level-2 Model (Faculty)

$$\pi_{0jk} = \beta_{00k} + r_{0jk}$$

$$\pi_{1jk} = \beta_{10k}$$

$$\pi_{2jk} = \beta_{20k}$$

Level-3 Model (College)

$$\beta_{00k} = \gamma_{000} + u_{00k}$$

$$\beta_{10k} = \gamma_{100}$$

$$\beta_{20k} = \gamma_{200}$$

where CCE represents accumulated college-level units earned with a grade of C or higher in the subsequent year.[9] The results displayed in Table 8 indicate that on average, Statway students were significantly more likely to earn college credits than the comparison students (with the higher event rate ratio, 1.37). The estimated accumulated credits were 5.57 vs. 4.08, respectively. We again found variation among colleges (Variance = 0.320). Figure 4 depicts that in the majority of colleges, Statway students earned more college credits in the subsequent year than the matched students.

[7] We also ran a four-level model and obtained similar results.
[8] HLM 7 applies penalized quasi-likelihood estimation to a three or higher level Poisson model.
[9] There were three quarter colleges, and accordingly, their college-level units were converted into semester units by dividing the units by 1.5.

Subgroup Analyses

To examine possible differential effects of Statway by (a) gender and race/ethnicity subgroups and by (b) math placement levels, we formulated a three-level HLM similar to those described above.[10] In these subgroup analyses, however, we applied effect coding to the grouping variables in order to accurately capture the main and interaction effects on the outcome. As reference categories, female, White, and a math placement three or more levels below college were coded as -1. Data regarding the unknown gender status and the college math placement level were excluded from these HLM analyses.

For the gender and race/ethnicity subgroup analyses, we formulated four models: (a) a base model (including a propensity score as covariate), (b) a main effect model (with the Statway, gender, and race/ethnicity main effects), (c) a two-way interaction effect model of Statway by gender and race/ethnicity, and (d) a three-way interaction effect model (i.e., Statway x gender x race/ethnicity). For the analyses with math placement levels, we formulated three models: (a) a base model, (b) a main effect model, and (c) a two-way interaction effect model of Statway by math placement level.

For each set of the analyses, those models were hierarchically related to one another and subjected to likelihood ratio tests. Table 9 presents these results.[11] We found significant main effects of gender and race/ethnicity for both Year 1 and Year 2 ($\chi^2(5) = 58.59$, $p < .001$; $\chi^2(5) = 44.87$, $p < .001$). We also obtained significant Statway by math placement level interaction effects for both Year 1 and Year 2 ($\chi^2(3) = 28.13$, $p < .001$; $\chi^2(5) = 17.27$, $p < .001$).

Consistent with the likelihood ratio test results, Tables 10 and 11 indicate significant main effects of Statway and race/ethnicity on the success rate. Figure 5 presents the estimated probabilities of success by gender and race/ethnicity. In general, Statway effects appear consistent for all subgroups of students. Tables 12 and 13 and Figure 6 break down the same results by math placement level, demonstrating the similar effects of Statway. The only exception was a somewhat smaller effect among Year 1 students who were placed one level below college level. It is worth mentioning that even after taking into account other main effects and interaction effects, the Statway main effect size was still the largest, as evidenced in the odds ratios of 2.27, 2.64, 2.25, and 2.69 (see Tables 10, 11, 12, and 13).

Similarly, we examined whether Statway effects on the college credit accumulation are different across the aforementioned subgroups. These results are presented in Tables 14 and 15 for gender and race/ethnicity and math placement level, respectively. We found significant interaction effects of Statway for gender and race/ethnicity as well as for math placement subgroups. Figure 7 presents the estimated college credit accumulation by gender and race/ethnicity and math placement level. The upper panel illustrates positive effects of Statway for each major race/ethnicity group: Black, Hispanic, and White. The lower panel indicates that regardless of math placement levels, overall, Statway students performed better than the comparison students. The effect appears the largest among students who were placed two levels below college level.

[10] We also ran four-level HLM analyses and found similar results.
[11] Because the penalized quasi-likelihood approach was used for estimating effects on college credit accumulation, the likelihood ratio test was not conducted.

Sensitivity Analyses

In general, Statway effects were strong and prevalent for all subgroups. The validity of these effects was based on an assumption of strongly ignorable treatment assignment. In other words, all relevant covariates were included in the propensity score analysis so that the bias due to unmeasured covariates could be ignored. Thus, we examined the sensitivity of the estimated Statway effects to possible confounding by unmeasured variables (Hong & Raudenbush, 2005, 2006; Lin, Psaty, & Kronmal, 1998; Rosenbaum, 1986). Given some unmeasured covariates (U), the Statway effect (δ) can be re-estimated by adjusting for some hypothesized hidden bias ($\gamma(\mathrm{E}[U_1]-\mathrm{E}[U_0])$) as:

$$\delta^* = \delta - \gamma(\mathrm{E}[U_1]-\mathrm{E}[U_0])$$

where γ is the unmeasured covariates' association with the outcome and $\mathrm{E}[U_1]-\mathrm{E}[U_0]$ is their association with treatment assignment (i.e., Statway or non-Statway enrollment).

Adapting the approach of Hong and Raudenbush (2005, 2006), we operationally defined a proxy for γ as a coefficient derived from a three-level model designed to predict the outcome with the same set of covariates used in the propensity score analysis and $\mathrm{E}[U_1]-\mathrm{E}[U_0]$ as the observed mean difference between the Statway and non-Statway groups on the corresponding covariate (for the set of covariates, see Tables 2 and 3). We then selected the largest positive value of the product of these two values as the largest possible bias[12] and obtained an adjusted Statway estimate (δ^*). Accordingly, we re-estimated Statway effects on the college math achievement in Year 1 and Year 2 and on the college credit accumulation in Year 1 and constructed 95 percent confidence intervals for each new estimate.

Table 16 presents the original Statway effect estimate, its adjusted estimate, and the 95 percent confidence interval of the adjusted estimate for each student outcome. As can be seen in this table, with adjustments for the largest hidden bias, none of the confidence intervals for the new Statway effect estimates contained 0 or any negative values, thereby supporting the strong ignorability assumption. Thus, it is very unlikely that our general conclusion regarding the positive effects of Statway on the student outcomes has been influenced by the omission of unmeasured confounding factors.

[12] We used the sum of the product values for those requiring a set of dummy variables (e.g., race/ethnicity, math placement level).

DISCUSSION

The current study sought to undertake a rigorous causal analysis of Statway's efficacy for community college students. To assess this effectiveness, we used a propensity score matching technique with a hierarchical linear modeling approach and formulated a more rigorous comparison group. Given the relatively small size of each Statway cohort compared to other developmental math students at each college, we were able to show a high degree of propensity score matching in 44 different indicators. Given the large size of the estimated effects, we conclude that there is robust evidence of Statway accelerating student success in acquiring college-level math credit. Not only did were we able to replicate our results across two Statway cohorts, but we were also able to replicate them across students within different gender and race/ethnicity groups as well as those within different math placement levels. Furthermore, our findings suggest that the Statway effect persists even after students complete the program: Statway students tended to accumulate more college credits with a grade of C or higher than their non-Statway counterparts.

In conclusion, these overall Statway results are very promising. However, we did detect some variation in outcomes among colleges. Accordingly, we need to further investigate how local context conditions affect Statway performance and use this information in order to formulate improvement strategies. As follow-up data become available to us, we also want to examine post-Statway performance for the Year 2 cohort to see if post-Statway success replicates across cohorts. Another direction for future research is to follow Statway students who transferred to a four-year university and examine their long-term performance. This analysis will further illuminate the dimensions and possible limitations of Statway's effectiveness.

REFERENCES

Austin, P. C. (2011). Optimal caliper widths for propensity-score matching when estimating differences in means and differences in proportions in observational studies. *Pharmaceutical Statistics, 10,* 150-161.

Bailey, T., Jeong, D. W., & Cho, S.-W. (2010). Referral, enrollment, and completion in developmental education sequences in community colleges. *Economics of Education Review, 29*, 255–270.

Boaler, J. (1998). Open and closed mathematics: Student experiences and understandings. *Journal for Research in Mathematics Education, 29,* 41-62.

Bryk, A. S., Gomez, L. M., & Grunow, A. (2011). Getting ideas into action: Building networked improvement communities in education. In M. T. Hallinan (Ed.), *Frontiers in sociology of education* (pp. 127-162). New York, NY: Springer.

Cullinane, J., & Treisman, P. U. (2010, September). *Improving developmental mathematics education in community colleges: A prospectus and early progress report on the Statway Initiative.* Paper presented at the National Center for Postsecondary Research Developmental Education Conference: What Policies and Practices Work for Students?, New York, NY. Retrieved from http://www.postsecondaryresearch.org/conference/PDF/NCPR_Panel4_CullinaneTreismanPaper_Statway.pdf

Dolle, J. R., Gomez, L. M., Russell, J. L., & Bryk, A. S. (2013). "More than a network: building communities for educational improvement." In B. J. Fishman, W. R. Penuel, A. R. Allen, & B. H. Cheng (Eds.), *Design-based implementation research: Theories, methods, and exemplars.* National Society for the Study of Education Yearbook. New York, NY: Teachers College Record.

Ericsson, K. A. (2008). Deliberate practice and acquisition of expert performance: A general overview. *Academic Emergency Medicine, 15,* 988-994.

Ericsson, K. A., Krampe, R. T., & Tesch-Römer, C. (1993). The role of deliberate practice in the acquisition of expert performance. *Psychological Review, 100,* 363-406.

Hiebert, J., & Grouws, D. (2007). The effects of classroom mathematics teaching on students' learning. In F. K. Lester Jr. (Ed.), *Second handbook of research on mathematics teaching and learning* (pp. 371–404). Charlotte, NC: Information Age.

Hong, G., & Raudenbush, S. W. (2005). Effects of kindergarten retention policy on children's cognitive growth in reading and mathematics. *Educational Evaluation and Policy Analysis, 27,* 205-224.

Hong, G., & Raudenbush, S. W. (2006). Evaluating kindergarten retention policy: A case study of causal inference for multilevel observational data. *Journal of the American Statistical Association, 101,* 901-910.

Lin, D. Y., Psaty, B. M., & Kronmal, R. A. (1998). Assessing the sensitivity of regression results to unmeasured confounders in observational studies. *Biometrics, 54,* 948-963.

Ming, K., & Rosenbaum, P. (2000). Substantial gains in bias reduction from matching with a variable number of controls. *Biometrics, 56,* 118-124.

Pashler, H., Rohrer, D., Cepeda, N. J., & Carpenter, S. K. (2007). Enhancing learning and retarding forgetting: Choices and consequences. *Psychonomic Bulletin & Review, 14,* 187-193.

Raudenbush, S. W., & Bryk, A. S. (2002). *Hierarchical linear models: Applications and data analysis methods* (2nd ed.). Thousand Oaks, CA: Sage Publications.

Raudenbush, S. W., Bryk, A. S., Cheong, Y. F., Congdon, R. T., & du Toit, M. (2011). *HLM 7: Hierarchical linear and nonlinear modeling.* Lincolnwood, IL: Scientific Software International.

Rosenbaum, P. R. (1986). Dropping out of high school in the United States: An observational study. *Journal of Educational Statistics, 11,* 207-224.

Rosenbaum, P. R., & Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika, 70,* 41-55.

Rosenbaum, P. R., & Rubin, D. B. (1985). Constructing a control group using multivariate matched sampling methods that incorporate the propensity score. *The American Statistician, 39,* 33-38.

Schmidt, R.A., & Bjork, R.A. (1992). New conceptualizations of practice: Common principles in three paradigms suggest new concepts for training. *Psychological Science, 3,* 207-217.

Strother, S., Van Campen, J., & Grunow, A. (2013). *Community College Pathways: 2011-2012 Descriptive Report.* Stanford, CA: Carnegie Foundation for the Advancement of Teaching.

Van Campen, J., Sowers, N., & Strother, S. (2013). *Community College Pathways: 2012-2013 Descriptive Report.* Stanford, CA: Carnegie Foundation for the Advancement of Teaching.

Table 1

Demographic Information of the First and Second Cohorts of Statway

	Year 1	Year 2
Mathematics Placement Level		
College Level	4.30%	4.60%
1 level below college level	17.60%	14.40%
2 levels below college level	51.80%	46.10%
3 or more levels below college level	26.30%	34.90%
Reading Placement Level		
College Level	51.90%	51.50%
1 level below college level	39.20%	33.20%
2 levels below college level	7.10%	10.30%
3 levels below college level	1.80%	5.00%
Gender		
Female	59.90%	59.80%
Male	40.10%	40.20%
Race/Ethnicity		
African American	24.70%	24.00%
Hispanic	33.10%	32.50%
Caucasian	29.20%	33.30%
Other	13.00%	10.20%
Home Language Growing Up		
English only	55.50%	60.30%
English and another language	32.40%	28.50%
Non-English language only	12.10%	11.20%
Maternal Education		
Less than high school	16.00%	14.20%
High school graduate or GED	31.40%	27.10%
Some college but no degree	24.30%	27.40%
2-year college degree	8.00%	12.00%
4-year college degree	12.80%	14.00%
Graduate or professional degree	7.50%	5.30%

Note. Adapted from Strother et al. (2013) and Van Campen et al. (2013)

Table 2

Descriptive Statistics of Covariates in the Two-Level Propensity Model - Year 1

Covariate	Non-Statway		Statway
	Before matching	After matching	
	%	%	%
Cohort			
First year*	57	43	40
Second year or older	43	57	60
Gender			
Female*	57	57	58
Male	43	43	42
Unknown	0	0	0
Race/Ethnicity			
Black	21	24	25
Hispanic	37	28	29
White*	29	32	29
Other	8	10	11
Unknown	5	6	6
Type of first-time student			
First-time college*	82	75	74
First-time transfer	18	25	26
Dual enrollment in a previous term			
Yes	4	4	4
No*	87	78	78
Unknown	9	18	18
Math placement level			
College Level	6	1	2
1 level below college level	18	17	15
2 levels below college level	35	43	43
3+ levels below college level*	26	21	21
Unknown	15	18	19
English placement level			
College level*	29	33	32
Developmental level	47	41	41
Unknown	24	26	27
Reading placement level			
College level*	31	33	32
Developmental level	39	33	33
Unknown	30	34	35

Part time vs. Full time						
Full time*	54		56		54	
Part time	46		44		46	
	M	***SD***	***M***	***SD***	***M***	***SD***
Age (in years)	23.15	7.32	25.58	9.78	26.08	10.25
Prior course enrollment and performance						
College math units attempted	0.05	0.56	0.06	0.57	0.06	0.61
College math units completed	0.02	0.34	0.02	0.28	0.02	0.31
College math courses attempted	0.02	0.17	0.02	0.18	0.02	0.20
College math courses completed	0.01	0.10	0.00	0.08	0.01	0.10
Developmental math units attempted	2.45	4.11	3.52	5.40	3.62	5.51
Developmental math units completed	1.39	2.76	1.93	3.45	1.95	3.74
Developmental math courses attempted	0.72	1.15	1.00	1.45	1.02	1.45
Developmental math courses completed	0.41	0.76	0.56	0.94	0.57	0.99
College non-math units attempted	7.57	13.25	12.92	19.23	13.90	20.18
College non-math units completed	5.58	10.78	9.74	15.83	10.71	16.63
College non-math courses attempted	2.53	4.29	4.21	6.00	4.52	6.11
College non-math courses completed	1.88	3.49	3.19	4.88	3.51	5.14
Developmental non-math units attempted	2.00	5.11	2.43	6.30	2.45	6.79
Developmental non-math units completed	1.59	4.33	2.04	5.51	2.02	5.76
Developmental non-math courses attempted	0.62	1.49	0.73	1.78	0.76	1.98
Developmental non-math courses completed	0.49	1.25	0.62	1.55	0.63	1.73
College STEM courses attempted	0.31	1.03	0.45	1.23	0.44	1.15
College STEM courses completed	0.21	0.82	0.28	0.89	0.28	0.86
College non-STEM courses attempted	2.21	3.84	3.76	5.52	4.09	5.69
College non-STEM courses completed	1.65	3.13	2.90	4.54	3.22	4.85
GPA of college STEM courses	2.01	1.35	1.97	1.35	2.05	1.32
GPA of college non-STEM courses	2.36	1.13	2.46	1.05	2.51	1.03
Missing on college STEM GPA	0.84	0.36	0.78	0.41	0.77	0.42
Missing on college non-STEM GPA	0.55	0.50	0.46	0.50	0.42	0.50

Note. Terms with "*" were used as reference categories (coded as 0, otherwise 1) when formulating dummy variables. First year under Cohort was defined as summer/fall enrollment in a given college for the first time in 2011 or 2012 for non-Statway or Statway. Part time vs. Full time status was based on fall 2011 or 2011 enrollment for non-Statway or Statway, with 12 or more units considered as full time. Age was computed by subtracting a birth year from 2011 or 2012 for non-Statway or Statway; in the current analyses, we centered Age around age 18. "Completed" was defined as course credit attained with a grade of C or higher (C- or higher if a college employs a +/– grading system) or Pass for developmental courses.

Table 3

Descriptive Statistics of Covariates in the Two-Level Propensity Model - Year 2

Covariate	Non-Statway		Statway
	Before matching	After matching	
	%	%	%
Cohort			
First year*	51	33	33
Second year or older	49	67	67
Gender			
Female*	58	61	60
Male	42	39	40
Unknown	0	0	0
Race/Ethnicity			
Black	23	25	25
Hispanic	38	30	29
White*	25	31	32
Other	8	9	9
Unknown	6	5	5
Dual enrollment in a previous term			
Yes	4	2	2
No*	85	79	76
Unknown	11	19	22
Math placement level			
College Level	4	2	2
1 level below college level	15	8	6
2 levels below college level	31	31	29
3+ levels below college level*	31	21	24
Unknown	19	38	39
English placement level			
College level*	27	19	19
Developmental level	45	30	31
Unknown	28	51	50
Reading placement level			
College level*	29	24	25
Developmental level	37	25	26
Unknown	34	51	49
Part time vs. Full time			
Full time*	48	52	54
Part time	52	48	46

	M	*SD*	*M*	*SD*	*M*	*SD*
Age (in years)	23.54	7.34	27.00	9.56	27.34	9.79
Prior course enrollment and performance						
College math units attempted	0.05	0.50	0.10	0.73	0.13	0.85
College math units completed	0.02	0.25	0.02	0.30	0.02	0.33
	%		%		%	
College math courses attempted						
0*	99		97		96	
1	1		2		3	
2 or more	0		1		1	
	M	*SD*	*M*	*SD*	*M*	*SD*
College math courses completed	0.01	0.07	0.01	0.08	0.01	0.08
Developmental math units attempted	2.71	3.97	3.23	4.35	3.20	4.50
Developmental math units completed	1.54	2.60	1.47	2.60	1.46	2.40
Developmental math courses attempted	0.83	1.20	0.98	1.31	0.95	1.32
Developmental math courses completed	0.47	0.77	0.45	0.78	0.44	0.71
College non-math units attempted	8.63	13.41	13.50	16.48	14.35	17.47
College non-math units completed	6.30	10.72	10.45	13.66	11.35	14.56
College non-math courses attempted	2.90	4.42	4.47	5.40	4.69	5.67
College non-math courses completed	2.11	3.46	3.44	4.37	3.66	4.56
Developmental non-math units attempted	2.12	4.10	1.73	3.82	1.68	3.79
Developmental non-math units completed	1.75	3.66	1.47	3.49	1.47	3.50
Developmental non-math courses attempted	0.68	1.31	0.53	1.17	0.52	1.16
Developmental non-math courses completed	0.56	1.16	0.45	1.06	0.45	1.05
College STEM courses attempted	0.36	0.84	0.43	0.91	0.43	0.89
College STEM courses completed	0.24	0.62	0.28	0.67	0.27	0.65
College non-STEM courses attempted	2.45	3.83	3.93	4.77	4.16	5.02
College non-STEM courses completed	1.82	3.12	3.10	4.02	3.34	4.23
GPA of college STEM courses	2.11	1.35	2.08	1.36	2.04	1.40
GPA of college non-STEM courses	2.30	1.13	2.52	1.03	2.59	0.98
Missing on college STEM GPA	0.79	0.41	0.75	0.43	0.76	0.43
Missing on college non-STEM GPA	0.53	0.50	0.42	0.49	0.42	0.49

Note. Terms with "*" were used as reference categories (coded as 0, otherwise 1) when formulating dummy variables. First year under Cohort was defined as summer/fall enrollment in a given college for the first time in 2011 or 2012 for non-Statway or Statway. Part time vs. Full time status was based on fall 2011 or 2011enrollment for non-Statway or Statway, with 12 or more units considered as full time. Age was computed by subtracting a birth year from 2011 or 2012 for non-Statway or Statway; in the current analyses, we centered Age around age 18. "Completed" was defined as course credit attained with a grade of C or higher (C- or higher if a college employs a +/– grading system) or Pass for developmental courses.

Table 4

Balance in Logit of the Propensity Score for non-Statway and Statway Students - Year 1

	Non-Statway						Statway		
	Sample before matching			Sample after matching					
College	***N***	***M***	***SD***	***N***	***M***	***SD***	***N***	***M***	***SD***
1	3463	-3.98	0.81	477	-3.18	0.92	97	-3.13	0.96
2	637	-3.25	0.72	171	-2.83	0.75	36	-2.72	0.90
3	3857	-4.15	0.61	385	-3.65	0.62	77	-3.65	0.62
4	2270	-3.74	0.51	320	-3.53	0.54	65	-3.50	0.61
5	2610	-3.93	0.48	286	-3.46	0.67	60	-3.40	0.74
6	1214	-3.16	0.79	341	-2.80	0.58	70	-2.76	0.64
7	2408	-4.12	0.82	254	-3.83	0.62	51	-3.82	0.64
8	1451	-3.71	0.79	228	-3.09	0.64	48	-3.00	0.72
9	2243	-3.70	0.65	341	-3.34	0.64	70	-3.28	0.73
10	3975	-4.61	0.54	240	-4.16	0.50	48	-4.17	0.49
11	8623	-5.67	1.07	255	-4.85	0.69	51	-4.85	0.69
12	6779	-4.76	0.58	340	-4.22	0.57	69	-4.16	0.62
13	4763	-5.40	0.50	110	-5.10	0.49	22	-5.10	0.50
14	8955	-5.21	0.54	280	-4.69	0.71	56	-4.69	0.72
15	2970	-4.76	0.78	171	-4.00	0.72	35	-3.96	0.76
16	714	-3.26	0.59	171	-2.91	0.55	36	-2.83	0.68
17	1102	-3.84	0.88	179	-3.18	1.01	37	-3.12	1.13
Total	58034	-4.66	1.02	4549	-3.65	0.93	928	-3.60	0.98

Table 5

Balance in Logit of the Propensity Score for non-Statway and Statway Students - Year 2

	Non-Statway						Statway		
	Sample before matching			Sample after matching					
College	***N***	***M***	***SD***	***N***	***M***	***SD***	***N***	***M***	***SD***
1	3517	-3.83	0.97	626	-2.94	0.93	126	-2.92	0.94
2	580	-3.78	1.02	115	-3.30	1.02	23	-3.31	1.02
3	3969	-4.33	0.96	418	-3.17	1.10	91	-3.01	1.20
5	2905	-4.34	0.86	280	-3.59	0.68	56	-3.59	0.68
6	987	-3.36	0.79	241	-2.64	0.64	50	-2.63	0.62
7	2129	-4.46	0.72	170	-3.50	0.31	34	-3.50	0.32
8	1618	-3.81	0.71	238	-2.98	0.82	51	-2.86	0.94
9	1976	-3.82	0.73	310	-2.80	0.60	62	-2.80	0.59
10	3902	-5.07	0.62	145	-4.58	0.69	30	-4.51	0.80
12	6999	-5.02	0.90	365	-4.38	1.09	73	-4.38	1.10
13	4613	-5.73	0.69	90	-4.93	0.69	18	-4.93	0.71
14	9994	-5.95	0.78	175	-5.48	1.05	35	-5.48	1.06
15	3317	-5.25	0.87	130	-4.33	0.78	26	-4.33	0.79
16	789	-2.99	0.79	104	-2.09	0.80	60	-1.89	0.91
17	1088	-4.03	1.13	176	-3.62	1.20	36	-3.56	1.28
Total	48383	-4.90	1.17	3583	-3.47	1.19	771	-3.34	1.26

Table 6

Model-Based Estimation of Statway Effect on College Math Achievement - Year 1

Fixed effect	**Coefficient**	***SE***	***t***	***p*-value**	**Odds ratio**
Intercept	-1.67	0.13	-13.06	<0.001	0.19
Propensity score	0.17	0.05	3.37	<0.001	1.19
Statway effect	1.67	0.08	20.84	<0.001	5.31
Random effect	**Variance**	***df***	χ^2	***p*-value**	
Level 3 (college)	0.239	16	153.32	< 0.001	
Level 2 (faculty)	0.014	24	31.43	0.142	

Note. The *df*'s, χ^2 *statistics*, and *p*-values of the random effects are for variance estimates derived from penalized quasi-likelihood estimation but reported here to indicate approximate significance levels.

Table 7

Model-Based Estimation of Statway Effect on College Math Achievement - Year 2

Fixed effect	**Coefficient**	***SE***	***t***	***p*-value**	**Odds ratio**
Intercept	-1.81	0.16	-11.27	<0.001	0.16
Propensity score	0.02	0.05	0.35	0.726	1.02
Statway effect	2.00	0.09	22.02	<0.001	7.40
Random effect	**Variance**	***df***	**χ^2**	***p*-value**	
Level 3 (college)	0.342	14	179.22	<0.001	
Level 2 (faculty)	0.000	21	17.53	>0.500	

Note. The *df*'s, χ^2 *statistics*, and *p*-values of the random effects are for variance estimates derived from penalized quasi-likelihood estimation but reported to indicate approximate significance levels.

Table 8

Model-Based Estimation of Statway Effect on Accumulated College Credits Earned in the Subsequent Year - Year 1

Fixed effect	**Coefficient**	***SE***	***t***	***p*-value**	**Event rate ratio**
Intercept	1.51	0.14	10.51	<0.001	4.52
Propensity score	-0.10	0.03	-3.09	0.002	0.90
Statway effect	0.31	0.11	2.89	0.004	1.37
Random effect	**Variance**	***df***	***χ2***	***p*-value**	
Level 3 (college)	0.320	16	373.82	<0.001	
Level 2 (faculty)	0.032	24	367.71	<0.001	

Table 9

Model Comparison of Subgroup Analyses on College Math Achievement

	Year 1			Year 2		
Gender and Race/Ethnicity	**χ^2**	***df***	***p*-value**	**χ^2**	***df***	***p*-value**
Base vs. Main	58.59	5	<0.001	44.87	5	<0.001
Main vs. Two-way	12.59	9	0.182	15.18	9	0.086
Two-way vs. Three way	3.16	4	0.531	3.50	4	0.477
Math placement level	**χ^2**	***df***	***p*-value**	**χ^2**	***df***	***p*-value**
Base vs. Main	27.43	3	<0.001	25.54	3	<0.001
Main vs. Two-way	28.13	3	<0.001	17.27	3	0.001

Note. χ^2 and df reflect differences in deviance statistics and the number of estimated parameters between two models, respectively.

Table 10

Model-Based Estimation of Statway, Gender, and Race/Ethnicity Effects on College Math Achievement - Year 1

Fixed effect	**Coefficient**	***SE***	***t***	***p*-value**	**Odds ratio**
Intercept	-1.40	0.14	-10.22	<0.001	0.25
Propensity score	0.21	0.05	4.00	<0.001	1.23
Statway	0.82	0.05	16.71	<0.001	2.27
Gender	-0.09	0.05	-1.87	0.062	0.91
Black	-0.50	0.09	-5.64	<0.001	0.60
Hispanic	-0.08	0.08	-1.00	0.318	0.92
Other	0.13	0.11	1.24	0.216	1.14
Unknown	0.26	0.13	1.91	0.057	1.29
Statway x Gender	-0.01	0.05	-0.19	0.849	0.99
Statway x Black	0.10	0.08	1.23	0.217	1.11
Statway x Hispanic	-0.01	0.08	-0.08	0.939	0.99
Statway x Other	-0.22	0.11	-2.09	0.037	0.80
Statway x Unknown	0.04	0.13	0.30	0.762	1.04
Gender x Black	-0.01	0.08	-0.13	0.901	0.99
Gender x Hispanic	-0.11	0.08	-1.47	0.143	0.89
Gender x Other	0.06	0.11	0.53	0.595	1.06
Gender x Unknown	0.05	0.13	0.37	0.711	1.05
SW x Gender x Black	0.01	0.08	0.10	0.918	1.01
SW x Gender x Hispanic	0.04	0.08	0.50	0.618	1.04
SW x Gender x Other	-0.04	0.10	-0.34	0.736	0.97
SW x Gender x Unknown	0.11	0.13	0.80	0.424	1.11
Random effect	**Variance**	***df***	***χ2***	***p*-value**	
Level 3 (college)	0.290	16	206.99	<0.001	
Level 2 (faculty)	0.007	24	29.07	0.217	

Note. The *df*'s, χ^2 *statistics*, and *p*-values of the random effects are for variance estimates derived from penalized quasi-likelihood estimation but reported here to indicate approximate significance levels.

Table 11

Model-Based Estimation of Statway, Gender, and Race/Ethnicity Effects on College Math Achievement - Year 2

Fixed effect	**Coefficient**	***SE***	***t***	***p*-value**	**Odds ratio**
Intercept	-1.47	0.15	-9.66	<0.001	0.23
Propensity score	0.03	0.05	0.75	0.451	1.03
Statway	0.97	0.06	16.31	<0.001	2.64
Gender	-0.02	0.06	-0.38	0.707	0.98
Black	-0.49	0.10	-4.77	<0.001	0.61
Hispanic	-0.04	0.09	-0.45	0.650	0.96
Other	0.22	0.13	1.67	0.095	1.24
Unknown	0.03	0.17	0.20	0.841	1.03
Statway x Gender	-0.06	0.06	-1.05	0.293	0.94
Statway x Black	0.13	0.10	1.35	0.178	1.14
Statway x Hispanic	-0.06	0.09	-0.71	0.477	0.94
Statway x Other	-0.18	0.13	-1.40	0.161	0.84
Statway x Unknown	0.05	0.17	0.29	0.773	1.05
Gender x Black	-0.04	0.10	-0.40	0.689	0.96
Gender x Hispanic	0.08	0.09	0.85	0.393	1.08
Gender x Other	-0.05	0.13	-0.37	0.714	0.95
Gender x Unknown	0.01	0.16	0.05	0.960	1.01
SW x Gender x Black	-0.12	0.10	-1.26	0.209	0.88
SW x Gender x Hispanic	-0.10	0.09	-1.14	0.254	0.90
SW x Gender x Other	0.07	0.13	0.57	0.569	1.08
SW x Gender x Unknown	0.22	0.16	1.36	0.174	1.25
Random effect	**Variance**	***df***	***χ2***	***p*-value**	
Level 3 (college)	0.311	14	162.03	<0.001	
Level 2 (faculty)	0.000	21	18.11	>0.500	

Note. The *df*'s, χ^2 *statistics*, and *p*-values of the random effects are for variance estimates derived from penalized quasi-likelihood estimation but reported here to indicate approximate significance levels.

Table 12

Model-Based Estimation of Statway and Math Placement Level Effects on College Math Achievement - Year 1

Fixed effect	**Coefficient**	***SE***	***t***	***p*-value**	**Odds ratio**
Intercept	-1.41	0.13	-10.61	<0.001	0.24
Propensity score	0.20	0.05	3.93	<0.001	1.23
Statway	0.81	0.04	18.68	<0.001	2.25
1 level below college level	0.16	0.10	1.69	0.092	1.18
2 levels below college level	0.03	0.07	0.43	0.668	1.03
Unknown	0.02	0.08	0.25	0.806	1.02
Statway x 1 level below	-0.40	0.08	-4.96	<0.001	0.67
Statway x 2 levels below	0.17	0.06	2.80	0.005	1.19
Statway x Unknown	0.04	0.08	0.54	0.592	1.04
Random effect	**Variance**	***df***	***χ2***	***p*-value**	
Level 3 (college)	0.275	16	201.37	<0.001	
Level 2 (faculty)	0.000	24	26.95	0.306	

Note. The *df*'s, χ^2 *statistics*, and *p*-values of the random effects are for variance estimates derived from penalized quasi-likelihood estimation but reported here to indicate approximate significance levels.

Table 13

Model-Based Estimation of Statway and Math Placement Level Effects on College Math Achievement - Year 2

Fixed effect	**Coefficient**	***SE***	***t***	***p*-value**	**Odds ratio**
Intercept	-1.50	0.17	-8.77	<0.001	0.22
Propensity score	0.06	0.05	1.11	0.269	1.06
Statway	0.99	0.06	17.78	<0.001	2.69
1 level below college level	0.43	0.14	3.09	0.002	1.54
2 levels below college level	-0.18	0.09	-2.05	0.041	0.84
Unknown	-0.05	0.09	-0.57	0.566	0.95
Statway x 1 level below	-0.24	0.13	-1.88	0.060	0.79
Statway x 2 levels below	-0.17	0.08	-2.13	0.034	0.84
Statway x Unknown	0.11	0.08	1.42	0.157	1.12
Random effect	**Variance**	***df***	***χ2***	***p*-value**	
Level 3 (college)	0.401	14	185.78	<0.001	
Level 2 (faculty)	0.000	21	14.23	>0.500	

Note. The *df*'s, χ^2 *statistics*, and *p*-values of the random effects are for variance estimates derived from penalized quasi-likelihood estimation but reported here to indicate approximate significance levels.

Table 14

Model-Based Estimation of Statway, Gender, and Race/Ethnicity Effects on Accumulated College Credits Earned in the Subsequent Year - Year 1

Fixed effect	Coefficient	*SE*	*t*	*p*-value	Rate ratio
Intercept	1.54	0.14	10.97	<0.001	4.66
Propensity score	-0.08	0.01	-9.41	<0.001	0.92
Statway	0.13	0.01	13.81	<0.001	1.13
Gender	-0.01	0.01	-1.52	0.127	0.99
Black	-0.22	0.02	-13.30	<0.001	0.80
Hispanic	0.02	0.01	1.46	0.144	1.02
Other	0.10	0.02	5.05	<0.001	1.11
Unknown	0.04	0.03	1.36	0.173	1.04
Statway x Gender	0.04	0.01	4.88	<0.001	1.05
Statway x Black	0.16	0.02	10.13	<0.001	1.17
Statway x Hispanic	-0.01	0.01	-0.78	0.434	0.99
Statway x Other	-0.18	0.02	-9.21	<0.001	0.83
Statway x Unknown	-0.03	0.03	-1.35	0.177	0.97
Gender x Black	-0.02	0.02	-1.48	0.140	0.98
Gender x Hispanic	-0.04	0.01	-2.67	0.008	0.96
Gender x Other	-0.11	0.02	-5.58	<0.001	0.89
Gender x Unknown	0.16	0.03	6.16	<0.001	1.17
SW x Gender x Black	0.01	0.02	0.94	0.350	1.01
SW x Gender x Hispanic	-0.06	0.01	-4.32	<0.001	0.94
SW x Gender x Other	-0.11	0.02	-5.58	<0.001	0.89
SW x Gender x Unknown	0.15	0.03	5.99	<0.001	1.17
Random effect	**Variance**	***df***	**$\chi 2$**	***p*-value**	
Level 3 (college)	0.319	16.00	364.03	<0.001	
Level 2 (faculty)	0.033	24.00	394.34	<0.001	

Table 15

Model-Based Estimation of Statway and Math Placement Level Effects on Accumulated College Credits Earned in the Subsequent Year - Year 1

Fixed effect	**Coefficient**	***SE***	***t***	***p*-value**	**Rate ratio**
Intercept	1.55	0.14	11.00	<0.001	4.69
Propensity score	-0.08	0.01	-9.56	<0.001	0.92
Statway	0.15	0.01	19.31	<0.001	1.16
1 level below college level	0.27	0.02	16.31	<0.001	1.31
2 levels below college level	0.07	0.01	5.80	<0.001	1.08
Unknown	-0.20	0.02	-12.73	<0.001	0.82
Statway x 1 level below	-0.05	0.01	-3.78	<0.001	0.95
Statway x 2 levels below	0.08	0.01	7.52	<0.001	1.09
Statway x Unknown	-0.05	0.02	-3.33	<0.001	0.95
Random effect	**Variance**	***df***	***χ2***	***p*-value**	
Level 3 (college)	0.322	16	403.32	<0.001	
Level 2 (faculty)	0.029	24	328.72	<0.001	

Table 16

Sensitivity Analyses on Statway Effect

	Original estimate	Adjusted estimate	95% CI
Year 1 - College math achievement	1.67	1.50	[1.34, 1.65]
Year 2 - College math achievement	2.00	1.97	[1.79, 2.15]
Year 1 - College credit accumulation	0.31	0.22	[0.01, 0.43]

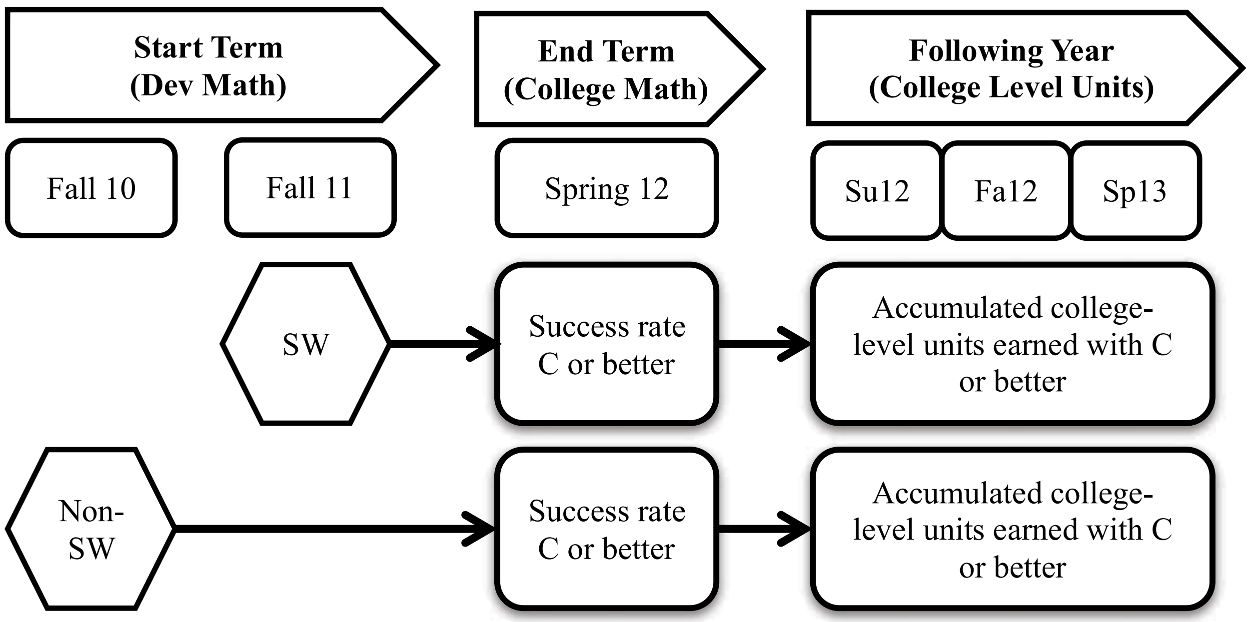


Figure 1. Study design. For Statway students, data were based on registrar reports from Statway classrooms. For non-Statway (Non-SW) students, results were based on whichever college-level math course, if any, was completed by spring 2012. If more than one course was completed during the two years, data from the course (minimum 3 units) with a higher grade were included. A grade of C- or higher was employed for six colleges that use a +/– grading system to define college math success and college-level units earned. Su12, Fa12, and Sp13 represent summer 2012, fall 2012, and spring 2013, respectively.

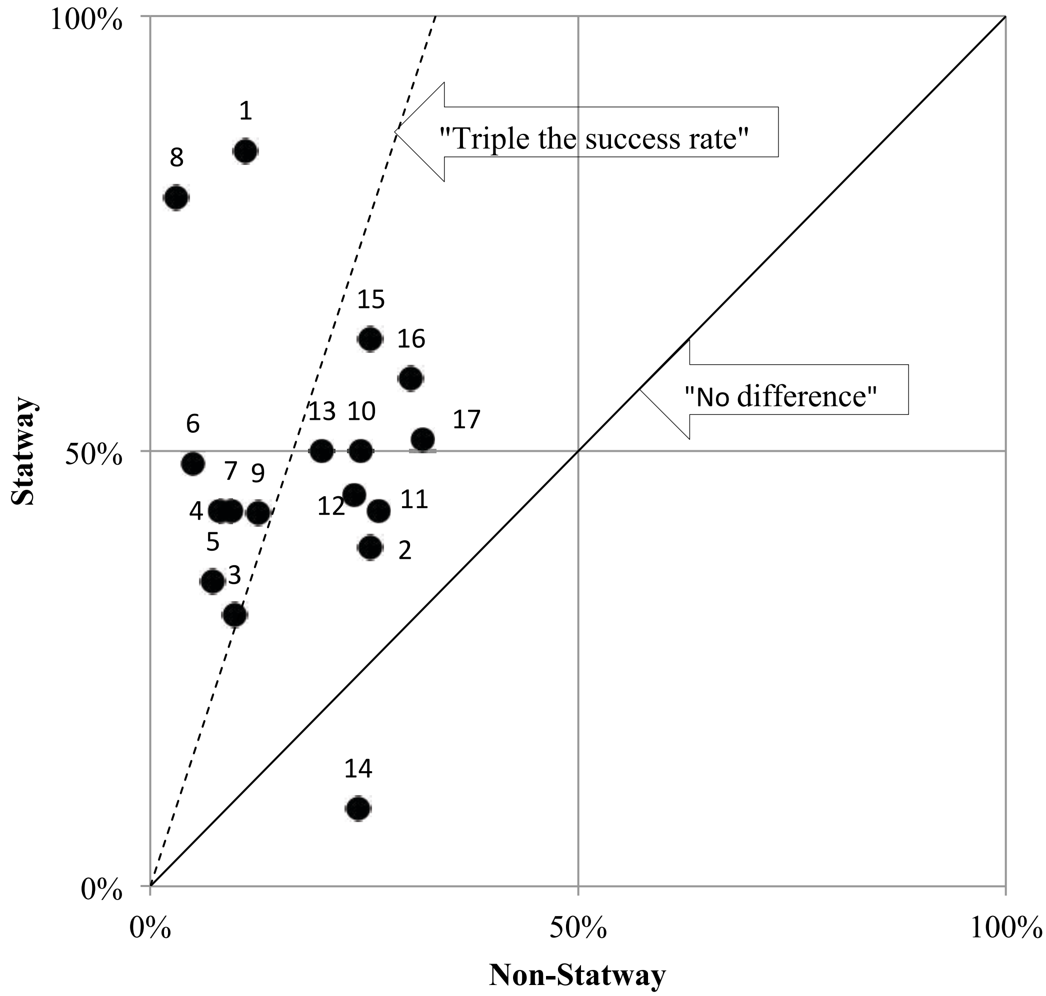


Figure 2. Comparative success rates by college - Year 1. The success rates of the matched comparison students are represented along the x-axis, and those of the Statway student are represented along the y-axis. For ease of interpretation, two reference lines are provided. The 45 degree solid line indicates no difference in outcome (Statway vs. Non-Statway). The dotted line represents "triple the success" rate of Statway students against their Non-Statway counterparts. The numeric values represent pseudo-college IDs.

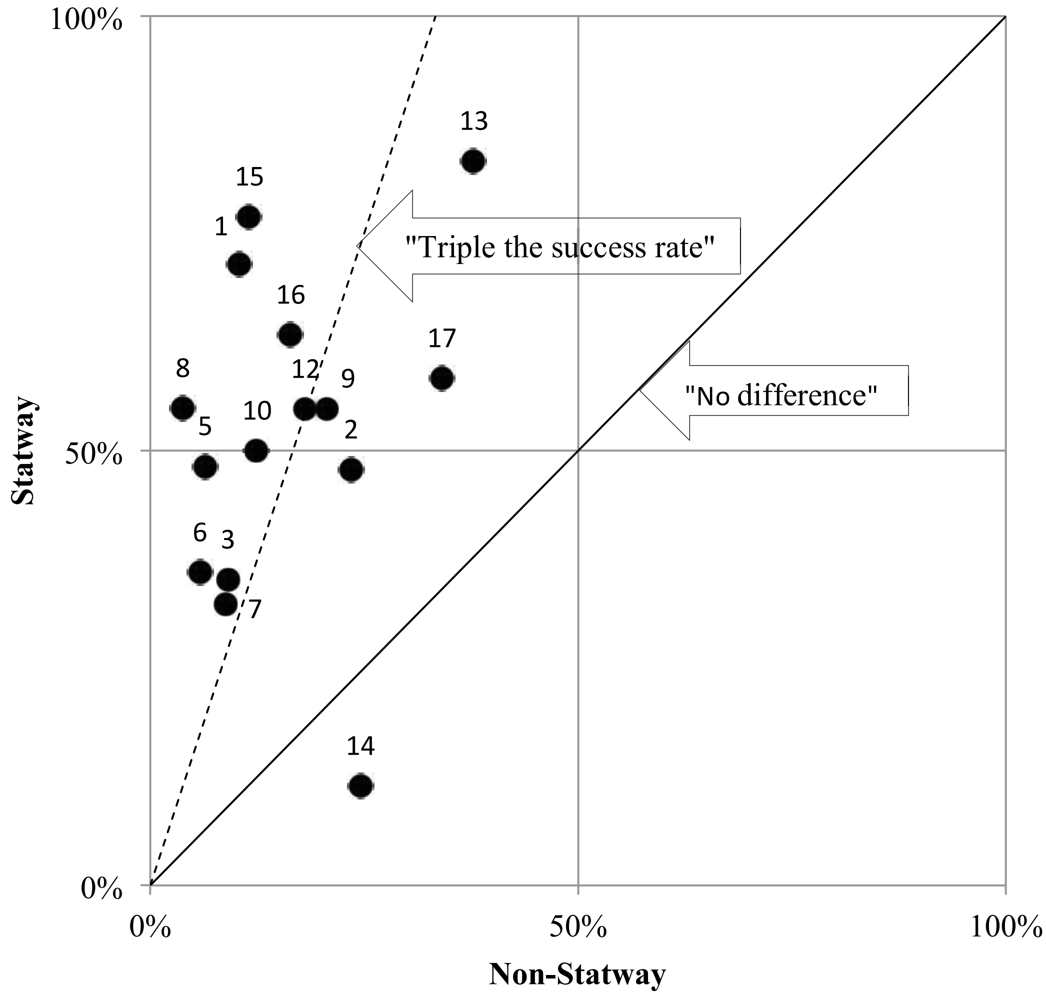


Figure 3. Comparative success rates by college - Year 2. The success rates of the matched comparison students are represented along the x-axis, and those of the Statway student are represented along the y-axis. For ease of interpretation, two reference lines are provided. The 45 degree solid line indicates no difference in outcome (Statway vs. Non-Statway). The dotted line represents "triple the success" rate of Statway students against their Non-Statway counterparts. The numeric values represent pseudo-college IDs.

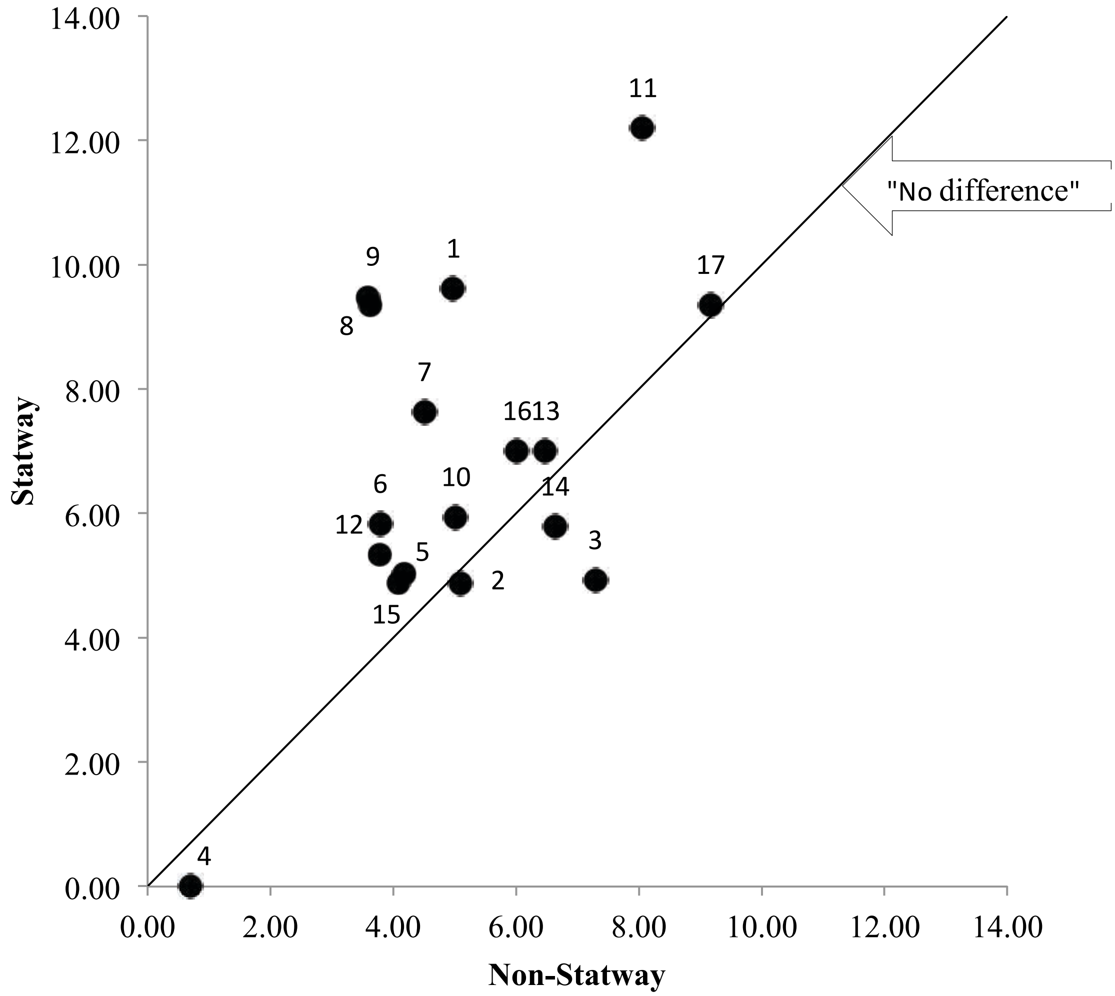
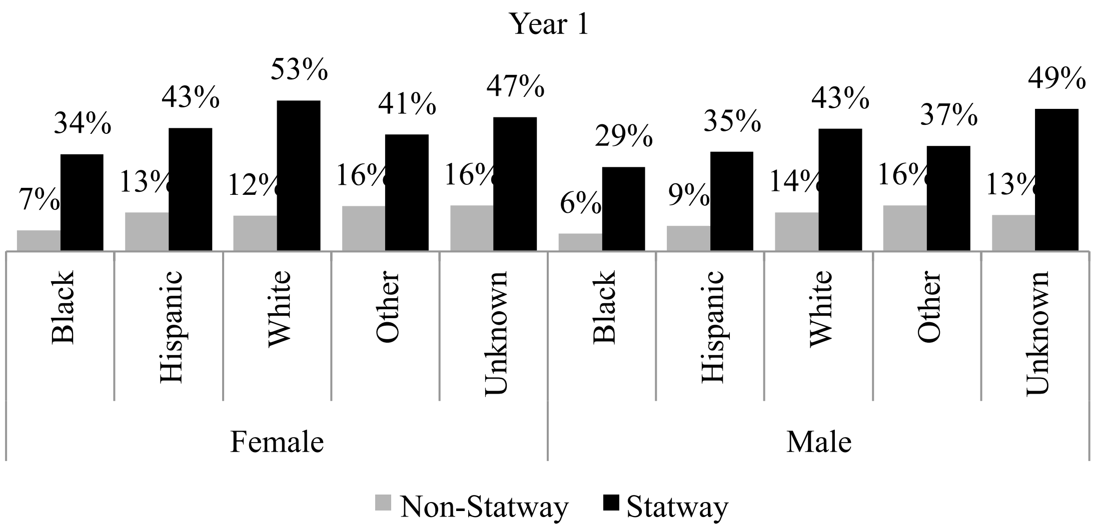


Figure 4. Comparative college-level credits accumulated in the subsequent year by college - Year 1. The college units of the matched comparison students are represented along the x-axis, and those of the Statway student are represented along the y-axis. For ease of interpretation, the 45 degree solid line indicates no difference in outcome (Statway vs. Non-Statway). The numeric values represent pseudo-college IDs.



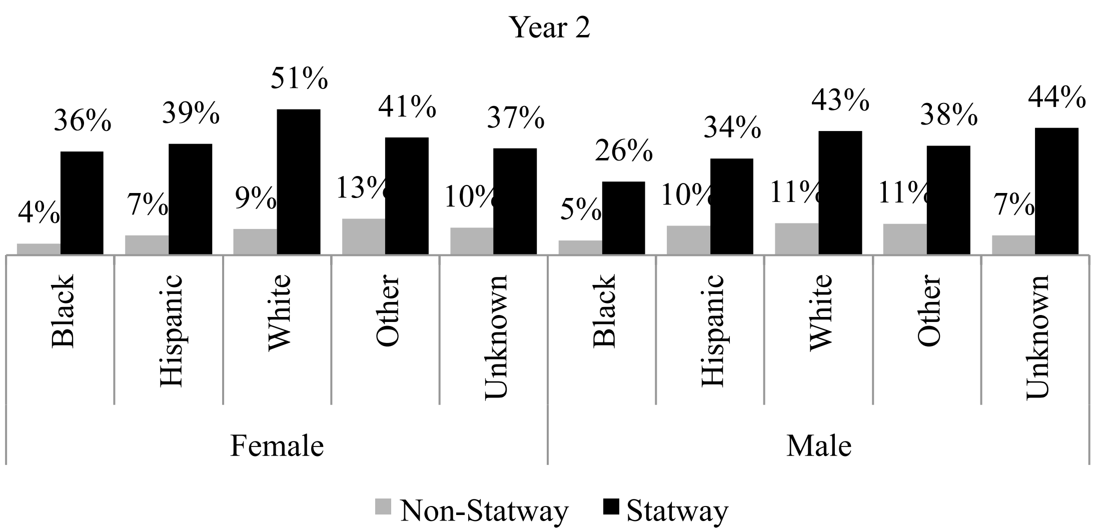


Figure 5. Model-based success rates by gender and race/ethnicity.

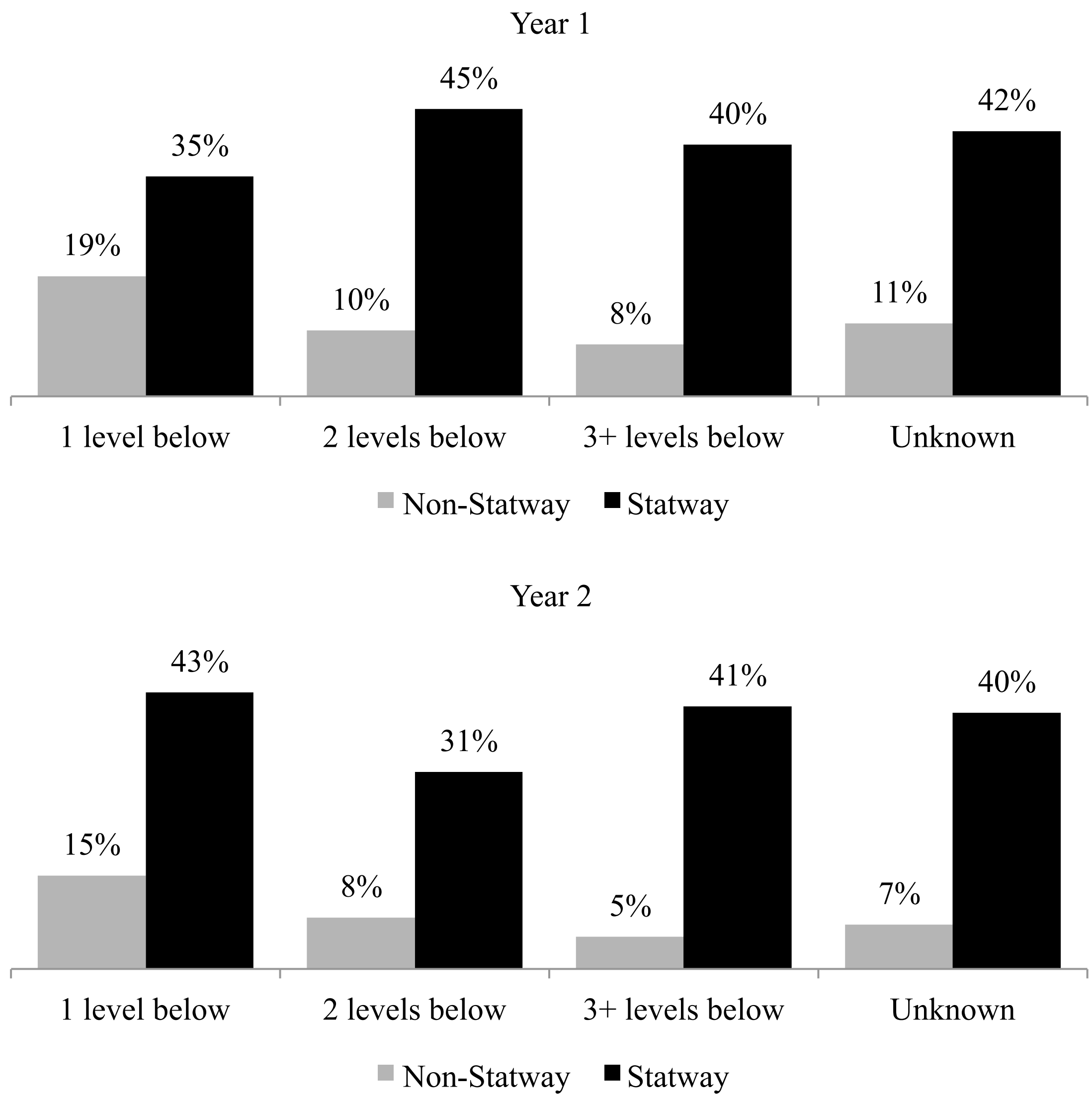


Figure 6. Model-based success rates by math placement level.

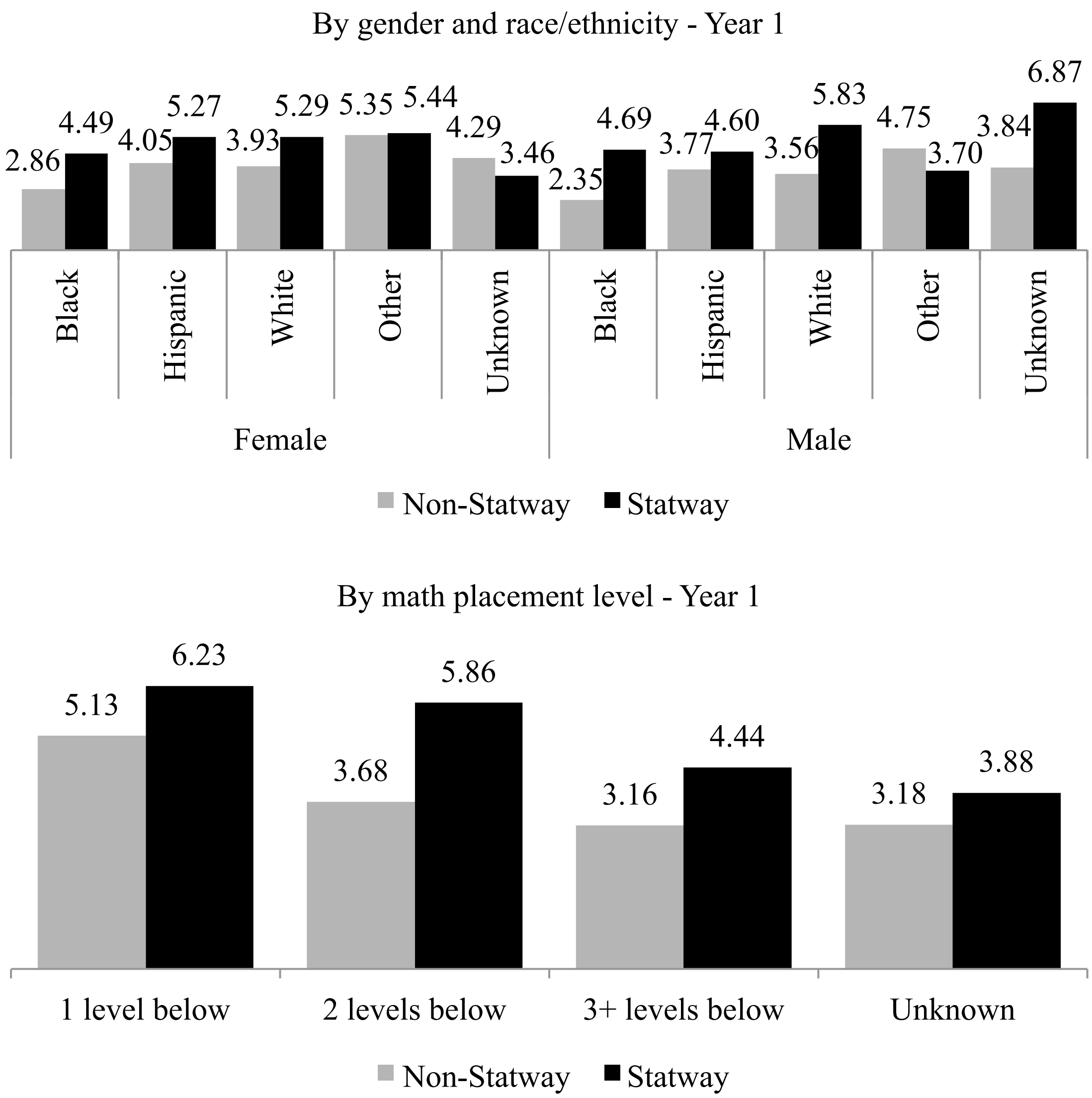


Figure 7. Model-based college-level credits accumulated in the subsequent year by gender and race/ethnicity (upper panel) and math placement level (lower panel) - Year 1.

Carnegie Foundation
for the Advancement of Teaching

This work is supported by Carnegie Corporation of New York, The Bill & Melinda Gates Foundation, The William and Flora Hewlett Foundation, The Kresge Foundation, and Lumina Foundation in cooperation with the Carnegie Foundation for the Advancement of Teaching.

The Carnegie Foundation for the Advancement of Teaching is committed to developing networks of ideas, individuals, and institutions to advance teaching and learning. We join together scholars, practitioners, and designers in new ways to solve problems of educational practice. Toward this end, we work to integrate the discipline of improvement science into education with the goal of building the field's capacity to improve.