Degree Attainment and Transfer among Statway© Students:
A Propensity Score Matched Analysis of Outcomes

Authors:
Jon R. Norman
Carnegie Foundation for the Advancement of Teaching

Hiro Yamada
Carnegie Foundation for the Advancement of Teaching

Melrose Huang
University of California, Berkeley

Corresponding Author:
Jon R. Norman
Carnegie Foundation for the Advancement of Teaching
51 Vista Lane
Stanford, CA 94305
(650) 566-5127
norman@carnegiefoundation.org

Abstract

Statway©, a two-course mathematics sequence designed for students to fulfill their developmental math requirements and earn college mathematics credit, has been shown to have a positive impact on students' completion of college math credit. The ultimate goal of Statway, however, is to improve longer term outcomes of transfer and degree completion. The current study uses a quasi-experimental propensity score matched design to examine student outcomes – transfer from a two-year to a four-year institution and two-year and/or four-year degree attainment – among students at six community colleges that offered Statway in the 2011 and 2012 academic years. The results show that Statway students earned degrees and transferred in greater proportions compared to similar students who enrolled in other developmental math options. In addition to examining all colleges together, each college was examined individually, showing that only some colleges had robust, statistically significant results. The differences seen in the analyses of each college separately likely reflect differences in the initial implementation of Statway, institutional priorities, state policies, and the local economies in which the colleges are situated. This analysis shows that, on average in the six schools for which data were available, enrollment in Statway increases the likelihood of transfer or degree completions and provides evidence of how an alternative to traditional developmental math can have a positive impact on students who often face strong headwinds completing educational goals.

Introduction

Statway©, a mathematics program designed to expedite the process by which students fulfill their developmental requirements and earn college mathematics credit, has been shown to improve the likelihood of completion of required math courses and credit accumulation (Yamada & Bryk, 2016; Huang & Yamada, 2017). However, until now, only preliminary evidence has been available concerning longer term outcomes. Prior research pointed to the likelihood of participation in Statway having a positive impact on degree completion and/or transfer to a four-year institution (Norman, 2017). Previous research used unmatched data from individual schools to compare degree and transfer rates for Statway students against all students within each school. The current analysis presents findings from a quasi-experimental design study that matched Statway and similar non-Statway students, and shows that Statway students earned degrees and transferred in greater proportions compared to similar students who enrolled in other developmental math options. Statway students also have higher probabilities of completing two-year and four-year degrees and of transferring compared to similar students who enrolled in other developmental mathematics courses.

This paper focuses on three student outcomes of interest: completion of a two-year degree or similar credential, transfer to a four-year institution, and completion of a four-year degree.[1] To assess Statway's impact on these outcomes among students at community colleges, Statway students from the first two cohorts were compared with similar students who did not enroll in Statway. Using propensity score matching to approximate a counter-factual comparison group, this study is able to estimate the impact of Statway enrollment on the outcomes of

[1] Students who completed a two-year degree, such as an associate's of arts or science, or completed a two-year diploma or certificate were included in the study as having obtained a degree. Less than 5% of all students who earned a credential from a community college received something other than an associate's degree of some sort. In the text, "two-year degree" is thus used as shorthand for all such outcomes.

interest. The paper first describes the Statway course in brief, and then examines the challenges related to developmental math and degree completion and transfer among community college students. Next, the data and methods employed are discussed, followed by the analysis and findings. Finally, the implications of the findings are discussed in the conclusion section.

Statway: An Alternative to Traditional Developmental Math

Statway aims to remove the barrier of traditional developmental math by offering students an alternative. Upon arrival at community college, about 60% of incoming students are referred to at least one developmental math course; 80% of these students do not earn college-level math credit even after three years (Bailey, Jeong, & Cho, 2010). When students do not complete college-level mathematics, they cannot complete degrees at two-year institutions, transfer to four-year institutions, or complete four-year degrees. As a result, hundreds of thousands of students are unable to progress toward their educational and life goals (Cullinane & Treisman, 2010).

Statway offers students an accelerated pathway by which they can meet their developmental mathematics requirements and achieve college-level mathematics credit in statistics within a single academic year. The theory behind the program's design is undergirded by six key drivers: 1) an accelerated pathway through college-level mathematics, 2) curriculum and instruction principles that emphasize productive struggle, explicit connections, and deliberate practice, 3) explicit integration of socioemotional supports in the classroom in the form of productive persistence, 4) language and literacy supports, 5) professional development for faculty, and 6) support of a networked improvement community comprised of researchers, practitioners, college administrators, and designers (LeMahieu, Grunow, Baker, Nordstrum, & Gomez, 2017).

Statway consists of a two-course sequence that combines content from developmental math and college-level statistics. Students work through both terms as a cohort and have the same faculty or instructional team in both terms. Students undertake project-based group work that uses mathematics and statistics to tackle problems relevant to students' lives. Upon completion of the two-course sequence, students have fulfilled the requirement for a college-level statistics course suitable for pursing a degree in a non-STEM (science, technology, engineering, and mathematics) area. Statway was designed as an alternative to traditional developmental math courses because such courses are associated with worse outcomes for students, including extremely high levels of noncompletion.

Overcoming the Barrier of Developmental Math

Graduation rates for those who start at community colleges are low. Most students in the United States who start at two-year institutions are unlikely to graduate either with a two-year degree or a four-year degree. Nationally, 30% of students who started at public two-year institutions in 2011 completed an associate's degree within six years (Shapiro et al., 2017). About 8% of students who started at public two-year institutions in 2011 completed a four-year degree during the same period (Shapiro et al., 2017). Similarly, a recent study estimates that only 23% of students at two-year institutions transfer to a four-year institution within five years, even though about 80% of entering community college students indicate their goal is to transfer to a four-year institution (Horn and Skomsvold, 2011).

One key reason students do not earn degrees or transfer is the requirement many face to complete developmental math or English courses that do not count towards graduation or transfer. Developmental math courses, in particular, constitute a barrier to success for many community college students. As noted previously, a large proportion of incoming community college students are identified as needing (remedial) developmental math, and most of those students do not complete such a course within three years (Bailey, Jeong, & Cho, 2010). Even students who do complete developmental mathematics courses (or sequences of courses) are less likely to graduate compared to other students (Bohlig et al., 2018). Students who take developmental math courses are also less likely to transfer to four-year institutions or subsequently earn bachelor's degrees as well. Even those who do complete their developmental math requirements seem to be less well prepared for subsequent study. Estimates vary of how strongly developmental math keeps students back, but students who complete more developmental math courses are less likely to graduate with an associate's degree, transfer to a four-year institution, or graduate with a bachelor's degree (Shields & Dwyer, 2017; Crisp & Delgado, 2014).

Not completing a degree matters considerably both to individual students and to society. Individuals who earn associate's degrees or certificates from two-year institutions earn more than their peers who do not hold similar credentials: on average, women with these credentials annually earn about $2,000 more than women with only a high school diploma, and on average, men with these credentials earn about $1,500 more than men with only a high school diploma (Jepsen, Troske, & Coomes, 2014). The advantage to earning a bachelor's degree is even greater. Individuals who have earned bachelor's degrees earn, on average, $21,000 more than individuals who hold only a high school diploma (U.S. Census Bureau, 2013). This gap will likely continue to grow in the future, as bachelor's degree holders have seen their earnings rise more (proportionally) compared to high school graduates since the early 1970s (Baum, 2014).

Data

The study included students from 6 colleges out of the original 19 that initially took part in Statway in 2011. Limitations in obtaining data resulted in a subset of colleges being included in this study. The data necessary to request National Student Clearinghouse (NSC) records for all Statway students were available from all 19 colleges, but data for comparison students were not. Requests were made of all colleges to provide the necessary data, but only six schools opted to provide the necessary information required for obtaining NSC data for comparison group students.

All students who enrolled in Statway or in a traditional development math course at the six institutions in the academic years 2011-12 or 2012-13 were included (N=39,275). Statway was offered in each of the six schools in each of the academic years included in this analysis. Offices of institutional research at the participating colleges provided data on students (demographics, social characteristics, and academic activities) at the time of initial enrollment in Statway or a developmental math course in fall of 2011 and fall of 2012. Data from the National Student Clearinghouse were obtained for students that indicated where and when students enrolled in school and any degrees earned during the five years following enrollment (inclusive of the initial enrollment year). A total of 30,733 students (90%) had follow-up data available for this analysis.

Students who were enrolled in Statway or a developmental math course during the 2011-12 academic year and students enrolled in Statway or a developmental math course during the 2012-13 academic year were both included.[2] For each cohort, five years of follow up data were

[2]In order to properly account for each Statway participant (and its matched comparison cases), it was determined that each individual would be retained in the cohort in which he or she initially entered the analysis. If, for example, if a Statway student entered the program in 2011 and did not complete the course, she was maintained

used so that each group of students had the same amount of time to earn a degree or transfer to a four-year institution. This time window differs from national statistics (cf. Shapiro et al., 2017), but was used (1) in the interest of learning about the impact of Statway sooner rather than later and (2) to give all students included in the study the same amount of time to achieve an outcome of interest.

Propensity Score Matching

To ensure that other factors that might contribute to a student transferring or earning a degree were accounted for and held constant between the two groups of students (Statway and non-Statway), a quasi-experimental study design with propensity score matching (PSM) was employed (Rosenbaum & Rubin, 1983). This resulted in creating two highly similar groups of students in terms of characteristics such as age, gender, and race/ethnicity, as well as on academic behavior, such as when and for how long they had been a student by the time of enrollment in Statway or a traditional developmental math course. Table 1 lists the covariates that were used in the matching process (along with the pre- and post-match descriptive statistics, discussed below).

This study utilized a two-level hierarchical linear model (HLM) to compute propensity scores for each student. The propensity scores were calculated based on data available at baseline—that is, student characteristics and records of academic activities available for 2011 or 2012. Propensity score matching is a statistical technique used to reduce selection bias—to reduce the influence of certain kinds of students being potentially more likely to have enrolled in Statway, leading to more positive outcomes than otherwise would have occurred—and,

as part of that cohort for subsequent longitudinal analyses - even if the student subsequently re-enrolled in Statway.

accordingly, to increase the validity of causal inference (Rosenbaum & Rubin, 1983). There are two main steps in PSM: first, a propensity score for each student is calculated (which is the likelihood of a student enrolling in Statway, regardless of whether s/he did so or not), and second, to match each student who did enroll in Statway with a student or students who did not based upon propensity scores that are of similar value (i.e., to match students with similar likelihood's of enrolling in Statway based on their known characteristics).

To obtain propensity scores, a two-level Bernoulli model was formulated and its model parameters estimated 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:

Figure 1: HLM Model Used in Propensity Score Matching

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)

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

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

$$\ldots,$$

$$B_{33j} = \gamma_{330},$$

$B_{34j} = \gamma_{340} + u_{34j},$ where *SW* is a dummy variable indicating whether a given student was enrolled in Statway (coded as 1) or not (coded as 0), *COV1…COV34* are the set of propensity score covariates (see Table 1), and *i* and *j* denote student and college, respectively. We estimated one random slope, β_{34j}, for a dummy variable indicating placement two levels below college math. Preliminary analyses identified significant heterogeneity among colleges in this relationship**.** Consequently, the propensity score matching in each college was based on their local site-specific relationship for this one variable. Each cohort year was matched separately.

A total of 32 student-level covariates were chosen (refer to Table 1), including student background characteristics, prior course taking, and course completion data (during the two years prior to the Statway term), to generate propensity scores using HLM (Hong & Raudenbush, 2005, 2006; Raudenbush & Bryk, 2002; Yamada & Bryk, 2016). These covariates were selected based on previous research and advice from institutional researchers in the participating colleges. Student demographic and social characteristics were used in the model because they have been shown to influence student performance in developmental mathematics (Bailey et al., 2010). Prior course records were also included because they generally provide a more accurate proxy for students' professional and educational goals than declared academic intentions (Jenkins & Cho, 2012). Some data were not available in institutional records and were therefore treated as missing when matching students.

For the second step involving matching students by propensity score, a nearest neighbor matching algorithm was used to conduct propensity score matching separately for each of the six institutions (Rosenbaum & Rubin, 1983). This approach was employed in order to preserve as many Statway students as possible while drawing their closest matches from a large group of potential comparison group students. For each Statway student, we found up to five matches (a

5:1 matching ratio) in order to select the nearest matches from the non-Statway population without sacrificing precision (Ming & Rosenbaum, 2000). To achieve this, a caliper distance of up to 0.2 was employed as the maximum acceptable difference between matched students. Using this tight of a caliper mitigates the possibility of poor nearest neighbor matches – that is, matches with students who do not have very similar likelihoods of enrolling in Statway (Austin, 2011; Rosenbaum & Rubin, 1983).

Prior to matching, the study included 889 Statway students and 38,386 comparison group students. The process of matching students reduced the number of students included in the study to 4,393; of those, 750 had enrolled in Statway while the remainder had enrolled in a traditional developmental math course. The analytic sample retained 84% of Statway students from the original sample. As Table 1 shows, both before and after the matching, the Statway group had a slightly higher proportion of women and students who identified as black/African American, and Statway students were slightly older than non-Statway students. The matched sample improved upon the unmatched sample in a number of ways: it eliminated imbalances in the proportion of students who are male and the proportion of students across other race/ethnicity categories than black/African American. It also reduced sample imbalances in the number of prior courses attempted and completed by students.

Table 1: Characteristics for PSM

Descriptive Statistics of Covariates in the Two-Level Propensity Model

	Sample before matching		Sample after matching	
	Non-Statway	Statway	Non-Statway	Statway
	%	%	%	%
Sex				
Female*	55	59	56	59
Male	41	37	38	37
Unknown	4	4	6	4
Race/Ethnicity				
Asian	8	5	5	5
Black	14	22	20	22
Hispanic	40	34	33	33
White*	25	24	25	25
Multiracial	<1	<1	<1	<1
Other	1	2	2	2
Unknown	12	13	15	13
Any course records in past two years				
No*	35	35	33	33
Yes	65	65	67	67

Note. "*" denotes covariates that served as reference categories (coded as 0) for creating dummy variables. Ages were centered around age 18 in the propensity score model. In terms since first developmental math course, 0 indicates that a student took her/his first developmental math course (including Statway) in the term concurrent with the Start term, and 1 indicates one term before the Start term, etc. Course load represents the total number of courses a student was enrolled in while taking the first Statway course within the sequence; for comparison group students, it refers to the total number of courses a student was enrolled in during the Start term. Success rates were calculated by dividing the total number of courses successfully completed over the total number of attempted courses. In this case, success was defined as receiving a grade of C or higher (C- or higher in schools that used +/- grading systems) or pass within a pass/fail grading scheme.

Table 1 continued

	M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Age (in years)	21.29	8.18	24.51	11.07	6.26	10.92	6.34	10.84
Terms since first developmental math course	1.84	2.54	2.01	2.71	2.12	2.71	1.97	2.70
Course load	3.38	1.43	3.28	1.35	3.34	1.42	3.28	1.35
Developmental math								
One level below college level								
Number of courses attempted	0.19	0.53	0.13	0.47	0.17	0.52	0.12	0.46
Success rate	0.05	0.21	0.02	0.14	0.03	0.16	0.02	0.12
Two levels below college level								
Number of courses attempted	0.28	0.59	0.30	0.72	0.31	0.65	0.30	0.72
Success rate	0.15	0.35	0.06	0.23	0.13	0.32	0.06	0.24
Three or more levels below college level								
Number of courses attempted	0.37	0.72	0.45	0.82	0.48	0.82	0.44	0.83
Success rate	0.20	0.39	0.24	0.41	0.26	0.42	0.24	0.41
Developmental English								
Number of courses attempted	0.14	0.49	0.11	0.45	0.13	0.50	0.11	0.45
Success rate	0.08	0.26	0.05	0.22	0.07	0.26	0.05	0.22
Developmental reading								
Number of courses attempted	0.05	0.29	0.03	0.22	0.03	0.24	0.03	0.22
Success rate	0.03	0.16	0.02	0.12	0.02	0.14	0.02	0.12
Developmental writing								
Number of courses attempted	0.10	0.42	0.07	0.33	0.07	0.33	0.08	0.34
Success rate	0.05	0.22	0.05	0.21	0.05	0.22	0.05	0.22
College math								
Number of courses attempted	0.01	0.14	0.02	0.19	0.02	0.19	0.02	0.20
Success rate	0.01	0.08	0.01	0.08	0.06	0.07	0.07	0.08
College non-math								
Number of courses attempted	2.27	4.39	3.53	6.02	3.30	5.44	3.29	5.55
Success rate	0.26	0.40	0.33	0.42	0.32	0.41	0.32	0.42
College STEM								
Number of courses attempted	0.20	0.78	0.30	0.90	0.36	1.24	0.29	0.90
Success rate	0.07	0.25	0.13	0.33	0.10	0.29	0.12	0.32
College non-STEM								
Number of courses attempted	2.08	4.14	3.25	5.72	2.95	5.06	3.01	5.24
Success rate	0.26	0.40	0.33	0.43	0.32	0.42	0.32	0.42

Analytic Strategy

The analysis focuses on three outcomes: completion of two-year degrees (or similar), transfer to four-year institutions, and completion of four-year degrees. To determine the effect of Statway on these outcomes, two analytic approaches were taken. First, t-tests were conducted for each outcome to compare the mean proportion of Statway and non-Statway students who achieved each of the three outcomes. Second, the likelihood of degree completion (two or four year) or transfer was estimated using logistic regression with fixed effects for institution attended and the year in which the student enrolled in Statway or a developmental math course.

The logistic regression model is presented below (Figure 2). The model included a dummy variable for participation in Statway (X_{sw}), the propensity score (X_{PS}, as an additional adjustment), and fixed effects for institution ($X_{INST1} – X_{INST5}$, dummy variables for each institution, with institution six as the reference category) and cohort (X_{COH}, dummy variable for year, with 2011 as the reference value). The model was specified identically for each outcome (π_{OUT}, separately, two-year degree/certificate, transfer to four-year institution, and four-year degree). Although a multilevel approach would have been more robust (Raudenbush & Bryk, 2002), with only six institutions it was not feasible.

Figure 2: Logistic Regression Model for Outcomes Analysis

$$logit(\pi_{OUT}) = \alpha + \beta_1 X_{SW} + \beta_2 X_{PS} + \beta_3 X_{INST1} + \cdots + \beta_7 X_{INST5} + \beta_8 X_{COH}$$

The two analyses were completed twice: once with the full sample and again for each of the six schools individually. The second set of analyses provides greater insight into variation in performance (Bryk et al., 2015), which is the examination of how individual contexts vary in contrast to the average effect found with the goal of learning from positive outliers to improve contexts with non-significant findings. While conducting t-tests on each schools' data remained straightforward, the small sample sizes and relatively rare occurrence of degree or transfer among Statway students (already only about 17% of each school's sample) necessitated using a different method for the multivariate analysis (King and Zeng, 2001). Thus, Firth's logistic regression model (which utilizes penalized log likelihoods rather than maximum log likelihoods) was employed to provide robust calculations of estimates (Firth, 1993).

Results

Differences between Statway and non-Statway Students at all Colleges

By taking into account other possible characteristics or experiences students had, the analysis is able to highlight the impact Statway had on student outcomes. A larger proportion of Statway students earned two-year and four-year degrees, or transferred to a four-year institution program, compared to their similar non-Statway peers (Table 2). The means for all three outcomes are statistically different between the two groups. The results presented in Table 3 show that Statway students were also considerably more likely to earn a two-year degree, transfer, or to earn a four-year degree compared to similar students who had enrolled in traditional developmental math. However, the results from the logistic regression indicate that there was considerable variation in these outcomes between schools (as indicated by the large variation in coefficients for the school fixed effects variables).

Table 2: Comparison of Means of Outcomes

Outcome	Group	N	Mean	*t* statistic	*df*	Pr(>|*t*|) (2-tailed)
Two-year degree	Statway Students	113	0.1506	-2.927	997.2	0.0035
	Non-Statway Students	399	0.1095			
Transfer	Statway Students	309	0.4120	-6.065	1029	0.0000
	Non-Statway Students	1,070	0.2937			
Four-year degree	Statway Students	66	0.0880	-4.311	906.3	0.0000
	Non-Statway Students	150	0.0411			

Table 3: Likelihood of Students Earning Degrees or Transferring Compared to Non-Statway Students

Outcome: Two-year degree

	Estimate	Log Odds	Std. Error	z value	Pr(>|z|)
intercept	-2.277	0.102	0.2875	-7.921	0.0000
Statway	0.4353	1.545	0.1237	3.517	0.0004
Propensity Score	0.6252	1.868	0.0776	8.050	0.0000
College 1	-1.321	0.266	0.4541	-2.909	0.0036
College 2	1.028	2.794	0.2280	4.505	0.0000
College 3	1.169	3.219	0.2243	5.211	0.0000
College 4	3.231	25.29	0.2478	13.03	0.0000
College 5	1.784	5.952	0.2112	8.443	0.0000
Cohort 2012	1.203	3.331	0.1128	10.66	0.0000

Outcome: Transfer

	Estimate	Log Odds	Std. Error	z value	Pr(>|z|)
intercept	-1.028	0.3575	0.1678	-6.126	0.0000
Statway	0.5330	1.704	0.0868	6.136	0.0000
Propensity Score	0.0279	1.028	0.0450	0.622	0.5342
College 1	1.921	6.831	0.1321	14.53	0.0000
College 2	0.0738	1.076	0.1144	0.645	0.5191
College 3	0.0488	1.050	0.1143	0.427	0.6692
College 4	0.3390	1.403	0.1423	2.381	0.0173
College 5	-0.2906	0.7477	0.1073	-2.707	0.0068
Cohort 2012	0.0872	1.091	0.0724	1.204	0.2285

Outcome: Four-year degree

	Estimate	Log Odds	Std. Error	z value	Pr(>|z|)
intercept	-3.870	0.0208	0.4024	-9.617	0.0000
Statway	0.7905	2.204	0.1552	5.090	0.0000
Propensity Score	0.1763	1.192	0.0972	1.813	0.0698
College 1	1.430	4.179	0.3129	4.569	0.0000
College 2	1.145	3.144	0.3064	3.739	0.0001
College 3	1.147	3.151	0.3054	3.758	0.0001
College 4	1.716	5.562	0.3405	5.039	0.0000
College 5	0.6845	1.982	0.3053	2.242	0.0249
Cohort 2012	0.5382	1.713	0.1485	3.624	0.0002

Variation in Performance among Individual Colleges

While the overall results of the analysis show Statway had a positive impact on degree and transfer outcomes, student outcomes varied considerably by school. In this section each colleges' outcomes are examined separately. The analysis here does not delve into the reasons for variation in outcomes, but it is important to note that the six schools are spread across five states (with two in one state) with differing local economies, that state policies vary considerably, and that student bodies at each school vary from one another. In addition, implementation of Statway differed somewhat between schools (Huang, Norman, & Yamada, 2018). However, implementation remained similar in terms of course content and pedagogy across institutions, with variation primarily due to differences in who was encouraged to enroll, course size, and other non-curricular aspects.

The data (in Table 4) show that colleges varied considerably on the proportions of Statway and non-Statway students that earned a degree and/or transferred to a four-year institution. Two of the colleges (Colleges 4 and 5) had statistically significantly greater proportions of students earn two-year degrees (or equivalent credentials). In the other four colleges, while outcomes tended to favor the Statway students, there were no statistically significant differences between Statway and non-Statway students. As noted above, differences between institutions and state policies may offer some explanation of these differences, as some states promote transfer over completion of a two-year degree (Dougherty, Reid, & Nienhusser, 2006)

Half of all Statway colleges included in this analysis had 10% or more of Statway students earn a four-year degree during the study period, while no college had a similar proportion of non-Statway students do so. Across the colleges, large proportions of both groups of students transferred, with statistically significantly greater proportions of Statway students transferring at Colleges 4 and 5 (the same two that had statistically significant differences in two-year degree completion).

Table 4: Comparison of Means for Outcomes, by College

College 1

Outcome	Group	N	Mean	*t* statistic	*df*	Pr(>|*t*|) (2-tailed)
Two-year degree	Statway Students	2	0.0222	-0.6845	111.3	0.4950
	Non-Statway Students	4	0.0109			
Transfer	Statway Students	264	0.7193	-0.2667	137.19	0.7900
	Non-Statway Students	66	0.7333			
Four-year degree	Statway Students	9	0.0790	-0.60314	126.25	0.5475
	Non-Statway Students	29	0.1000			

College 2

Outcome	Group	N	Mean	*t* statistic	*df*	Pr(>|*t*|) (2-tailed)
Two-year degree	Statway Students	9	0.1057	1.2219	197.2	0.2232
	Non-Statway Students	64	0.0731			
Transfer	Statway Students	40	0.2809	-0.9572	170.4	0.3398
	Non-Statway Students	170	0.3252			
Four-year degree	Statway Students	10	0.0528	-1.077	156.7	0.2829
	Non-Statway Students	32	0.0813			

College 3

Outcome	Group	N	Mean	*t* statistic	*df*	Pr(>|*t*|) (2-tailed)
Two-year degree	Statway Students	11	0.1180	1.173	206.5	0.2422
	Non-Statway Students	72	0.0852			
Transfer	Statway Students	40	0.2787	-0.7016	182.1	0.4838
	Non-Statway Students	170	0.3101			
Four-year degree	Statway Students	11	0.0524	-1.2482	164.0	0.2137
	Non-Statway Students	32	0.0852			

Table 4 (continued)

College 4

Outcome	Group	N	Mean	*t* statistic	*df*	Pr(>|*t*|) (2-tailed)
Two-year degree	Statway Students	34	0.2468	-4.522	78.64	0.0003
	Non-Statway Students	76	0.5574			
Transfer	Statway Students	27	0.3182	-1.792	81.92	0.0767
	Non-Statway Students	98	0.4426			
Four-year degree	Statway Students	10	0.0650	-1.987	70.77	0.0508
	Non-Statway Students	20	0.1639			

College 5

Outcome	Group	N	Mean	*t* statistic	*df*	Pr(>|*t*|) (2-tailed)
Two-year degree	Statway Students	53	0.1459	-3.131	279.3	0.0019
	Non-Statway Students	157	0.2431			
Transfer	Statway Students	94	0.1775	-7.130	271.5	0.0000
	Non-Statway Students	191	0.4312			
Four-year degree	Statway Students	21	0.0251	-3.460	242.2	0.0007
	Non-Statway Students	27	0.0963			

College 6

Outcome	Group	N	Mean	*t* statistic	*df*	Pr(>|*t*|) (2-tailed)
Two-year degree	Statway Students	4	0.0384	0.4348	192.5	0.6642
	Non-Statway Students	26	0.0310			
Transfer	Statway Students	42	0.2614	-1.434	173.3	0.1535
	Non-Statway Students	177	0.3255			
Four-year degree	Statway Students	5	0.0147	-1.356	147.4	0.1769
	Non-Statway Students	10	0.0388			

It is not surprising that not all institutions show significant differences between the two groups of students for all outcomes, even though the analysis with all schools combined shows significant differences. For many of the analyses, the differences within schools are too small to be statistically significant (i.e., the difference between Statway and non-Statway students who transferred at College 1). In other cases, the comparisons are not statistically significant because of the small numbers of students in the outcome categories (i.e., very few students in either group earned two-year degrees at College 1).

The findings from the logistic regression analysis conducted for each school individually follow the same pattern, with Colleges 4 and 5 again standing out (only results for Colleges 4 and 5 are presented here; results for other colleges are available from the authors). As with the comparisons shown in the proportions completing degrees or transferring, not all of the outcomes were statistically more likely for Statway students compared to non-Statway students. The strong impact of Statway at these schools may be due to a variety of factors, including the process for students selecting (or being selected) to enroll in Statway, the way in which Statway was implemented, or the particularities of the experiences of students during the study period.

Table 5: Logistic Regression Results for Colleges 4 and 5

College 4: Two-year Degrees

	Estimate	Log Odds	Std. Error	z value	Pr(>|z|)
intercept	1.260	3.526	0.7450	1.692	0.0907
Statway	1.388	4.009	0.2976	4.666	0.0001
Propensity Score	0.6802	1.974	0.2001	3.399	0.0007
Cohort 2012	0.6070	1.834	0.2602	2.333	0.0196

College 4: Transfer

	Estimate	Log Odds	Std. Error	z value	Pr(>|z|)
intercept	0.8297	2.292	0.6999	1.186	0.2358
Statway	0.5138	1.671	0.2885	1.781	0.0749
Propensity Score	0.3898	1.476	0.1842	2.117	0.0343
Cohort 2012	-0.1610	0.8512	0.2419	-0.666	0.5057

Table 5 (continued)

College 4: Four-year Degrees

	Estimate	Log Odds	Std. Error	z value	Pr(>|z|)
intercept	-2.341	0.0962	1.200	-1.950	0.0512
Statway	1.025	2.789	0.4171	2.459	0.0139
Propensity Score	0.0463	1.047	0.3135	0.148	0.8826
Cohort 2012	-0.3729	0.6887	0.4317	-0.864	0.3877

College 5: Two-year Degrees

	Estimate	Log Odds	Std. Error	z value	Pr(>|z|)
intercept	-5.735	0.0032	1.591	-3.604	0.0001
Statway	0.8034	2.233	0.2047	3.924	0.0001
Propensity Score	0.3946	1.483	0.2108	1.872	0.0082
Cohort 2012	5.910	36.87	1.408	4.196	0.0000

College 5: Transfer

	Estimate	Log Odds	Std. Error	z value	Pr(>|z|)
intercept	-2.206	0.1101	0.4393	-5.021	0.0002
Statway	1.257	3.518	0.1585	7.934	0.0001
Propensity Score	-0.1727	0.8413	0.1088	-1.587	0.1139
Cohort 2012	0.1369	1.146	0.1595	0.8581	0.3839

College 5: Four -ear degrees

	Estimate	Log Odds	Std. Error	z value	Pr(>|z|)
intercept	-10.05	0.0003	2.193	-4.584	0.0002
Statway	1.531	4.624	0.3067	4.993	0.0001
Propensity Score	-0.6441	0.5251	0.3951	-1.630	0.1139
Cohort 2012	4.930	13.84	1.443	3.415	0.3839

To test to see if the inclusion of Colleges 4 and 5 was responsible for the outcomes found in the overall analyses, the t-tests and logistic regression models were rerun for all schools together with students from Colleges 4 and 5 omitted (N=2,730). The t-tests show significant differences between Statway and non-Statway students for transfer (Statway mean = 0.3992, non-Statway mean = 0.3457; t = -2.162, df = 667.3, p-value = 0.0310) and for four-year degree attainment (Statway mean = 0.0743, non-Statway mean = 0.0456; t = -2.231, df = 599.8, p-value = 0.0260) but not for two-year degree attainment (Statway mean = 0.0552, non-Statway mean =

0.0735; $t = 1.539$, $df = 748.6$, p-value = 0.1242). The logistic regression model results indicate that in this subset of colleges, Statway students have a statistically significant greater likelihood of earning a four-year degree (log odds = 1.510, $SE = 0.2045$, $z = 2.329$, $p = 0.0199$) but are not significantly more likely to transfer or earn a two-year degree. Thus, Colleges 4 and 5 influence the overall results to a certain extent, primarily related to transfer rates and two-year credential completion.

Conclusion

The analyses included here show that students enrolling in the Statway course at the six colleges included had more positive outcomes related to degree completion and transfer than the comparable group of students who did not enroll in Statway. Further research is needed to understand if the continued spreading of Statway to other colleges (including four-year institutions), in other states, and implemented in different ways (cf. Huang, Norman, & Yamada, 2018), sustains the positive impact on Statway students compared to non-Statway students. Additionally, the findings here indicate that outcomes vary by college, which suggests that further understanding of how institutions implement Statway and of local contexts is needed. This constitutes an important area for further improvement, as networked improvement communities, of which Statway is an example, aspire to reduce variability in outcomes across network members (cf. Bryk, Gomez, Grunow, & LeMahieu, 2015).

As noted, students whom community colleges determined to be in need of developmental math generally have worse degree and transfer outcomes compared to other students (Bohlig et al., 2018). Among these six schools, Statway students are able to make greater progress than their peers. Similarly, Statway students earned bachelor degrees at about the same rate (8%) as all students nation-wide (Shapiro et al., 2017) and at a higher rate than that of the comparison students in this analysis. It is important to note that the national figures are based on all students, which includes the 40% of students who start at community colleges well-prepared for college level mathematics. What further makes the Statway outcomes compelling is that the national figures are for six-year periods whereas this study included only a five-year period due to data availability at this time. This means that the Statway figures are likely underestimates of the proportion of students who earned a degree for direct comparison to the national figures obtained following a six-year performance period. While the transfer outcomes are partially driven by particular schools that have high transfer rates, the overall numbers compare favorably with the national estimate of 23% (Crisp & Delgado, 2014).

The differences seen in the analyses of each college separately (as well as in the analysis of all colleges together) likely reflect differences in the initial implementation of Statway, institutional priorities, state policies, and the local economies in which the colleges are situated. Some institutions and states place a greater emphasis on two-year degree completion while others focus on transfer and four-year degree completion. Community colleges have differing levels of integration into their local economies, and the strength of that relationship influences two-year degree completion rates (Kalleberg & Dunn, 2015). States also make different funding decisions concerning community college priorities (Dougherty & Reid, 2007; Jenkins & Boswell, 2002). Even so, the analysis of the outcomes of the six colleges offering Statway included here provide evidence of how an alternative to traditional developmental math courses has had a positive impact on students who often face strong headwinds to attaining their educational goals.

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*(2)*,* 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*(2), 255–270.

Baum, S. (2014). Higher education earnings premium: Value, variation, and trends. *Urban Institute*.

Bohlig, E. M., Bullock, C. M., Garza, M., Hartman, C., Lovseth, K., & Yu, H. (2018). Developmental education and community college student success: Are the odds ever in their favor? Texas Education Review, 6(1), 53-74.

Bryk, A. S., Gomez, L. M., Grunow, A., & LeMahieu, P. G. (2015). Learning to improve: How America's schools can get better at getting better. Cambridge, MA: Harvard Education Press.

Crisp, G., & Delgado, C. (2014). The impact of developmental education on community college persistence and vertical transfer. *Community College Review*, *42*(2), 99-117.

Cullinane, J., & Treisman, P. U. (2010). Improving developmental mathematics education in community colleges: A prospectus and early progress report on the Statway Initiative. An NCPR Working Paper. *National Center for Postsecondary Research*.

Dougherty, K., Reid, M., & Nienhusser, H. K. (2006). *State policies to achieve the dream in five states: An audit of state policies to aid student access to and success in community colleges in the first five achieving the dream states*. New York: Columbia University, Teachers College, Community College Research Center.

Firth, D. (1993). Bias reduction of maximum likelihood estimates. *Biometrika, 80 (*1), 27-38.

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*(3)*,* 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*(475)*,* 901-910.

Horn, L., & Skomsvold, P. (2011). Community college student outcomes: 1994-2009. Washington, DC: National Center for Education Statistics.

Huang, M., and Yamada, H. (2017). Maintaining Success Rates: Does Statway® Sustain its Impact as it Scales to New Classrooms and Institutions? Carnegie Foundation for the Advancment of Teaching. Stanford, CA.

Huang, M., Norman, J., Yamada, H. (2018). Adaptation with Integrity: Origin and Evolution of Accelerating Statway® to a Single Term. Carnegie Foundation for the Advancment of Teaching. Stanford, CA.

Jenkins, D., & Boswell, K. (2002). *State Policies on Community College Remedial Education: Findings from a National Survey*. Denver, CO: Center for Community College Policy, Education Commission of the States, Denver, CO

Jenkins, D., & Cho, S. W. (2012). *Get with the program: Accelerating community college students' entry into and completion of programs of study* (CCRC Working Paper No. 32). New York, NY: Columbia University, Teachers College, Community College Research Center.

Jepsen, C., Troske, K., & Coomes, P. (2014). The labor-market returns to community college degrees, diplomas, and certificates. *Journal of Labor Economics*, *32*(1), 95-121.

King, G., & Zeng, L. (2001). Logistic regression in rare events data. *Political analysis*, *9*(2), 137-163.

Kalleberg, A. L., & Dunn, M. (2015). Institutional determinants of labor market outcomes for community college students in North Carolina. *Community College Review*, 43(3), 224-244

LeMahieu, P. G., Grunow, A., Baker, L., Nordstrum, L. E., & Gomez, L. M. (2017). Networked improvement communities: The discipline of improvement science meets the power of networks. *Quality Assurance in Education*, *25*(1), 5-25.

Ming, K., & Rosenbaum, P. (2000). Substantial gains in bias reduction from matching with a variable number of controls. *Biometrics, 56*(1), 118-124.

Norman, J. (2017). Pathways Post-Participation Outcomes: Preliminary Findings. Carnegie Foundation for the Advancement of Teaching. Stanford, CA.

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

Rosenbaum, P. R., & Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika, 70*(1)*,* 41-55.

Shapiro, D., Dundar, A., Huie, F., Wakhungu, P. K., Yuan, X., Nathan, A., & Bhimdiwala, A. (2017). *Completing college: A national view of student completion rates--fall 2011 cohor*t. (Signature Report No. 14). National Student Clearinghouse.

Shields, K. A., & O'Dwyer, L. M. (2017). Remedial education and completing college: Exploring differences by credential and institutional level. *The Journal of Higher Education*, *88*(1), 85-109.

U.S. Census Bureau (2013). *Income, Poverty and Health Insurance in the United States: 2012*, *table PINC-03.* Retrieved from http://www.census.gov/hhes/ www/income/data/index.html.

Yamada, H., & Bryk, A. S. (2016). Assessing the first two years' effectiveness of Statway®: A multilevel model with propensity score matching. *Community College Review*, *44*(3), 179-204.