Carnegie Foundation for the Advancement of Teaching

# Assessing the Effectiveness of Quantway

## A Multilevel Model with Propensity Score Matching

**October 2016**

**Hiroyuki Yamada, Angel Bohannon, & Alicia Grunow**

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.*

CARNEGIE MATH PATHWAYS

TECHNICAL REPORT

## ABSTRACT

Quantway is a Carnegie Math Pathways initiative which redesigns the content, pedagogy, and structure of traditional developmental math courses to simultaneously tackle traditional barriers of student success and support a broader range of developmental students in achieving their math potential. Specifically, Quantway is a quantitative reasoning sequence that is comprised of a single term developmental math course called Quantway 1 and a college-level math course called Quantway 2. This study assessed the effectiveness of the developmental math course, Quantway 1, during its first 6 semesters of implementation. We used a hierarchical linear modeling technique to conduct propensity score matching across 37 student characteristics in order to compare the course performance of Quantway 1 students with matched comparison students in traditional developmental math courses. Quantway 1 students demonstrated significantly higher odds of success than matched comparison students in fulfilling developmental math course requirements. Additionally, Quantway 1 effects were positive across all sex and race/ethnicity subgroups as well as in nearly all classrooms and colleges. This study provided robust evidence that Quantway 1 increases student success in fulfilling developmental math requirements and advances equity in student outcomes. Directions for future work are suggested.

Traditional developmental or remedial math sequences serve as a huge impediment for community college students, often preventing them from obtaining technical credentials and associate degrees, as well as blocking their transfer to four-year institutions. Nearly 60% of community college students nationwide are required to take at least one developmental mathematics course, and 80% of these students do not complete a college math course within three years (Bailey, Jeong, & Cho, 2010). Students spend long periods of time repeating courses and accruing student loan debt, ultimately leaving college without a degree.

This crisis in completion has negative ramifications for community college student earnings and for American workforce development overall. Students who do not complete higher levels of education have significantly lower incomes. In 2012, for all people aged 25 or older, high school graduates earned an annual income of $33,904, those with associate's degrees earned $40,820, and those with bachelor's degrees earned $55,432 (Johnstone, 2013). Lower levels of educational attainment also have a detrimental effect on the overall economy as technological advances and global competition have created a press for an increasingly skilled workforce. The Georgetown Center on Education and the Workforce estimates that 65% of all American jobs will require a postsecondary education beyond high school by 2020, but the United States will fall short of meeting these requirements by 5 million workers at the current rate of production (Carnevale, Smith, & Strohl 2013). Community colleges play a critical role in workforce development, serving half of the 6.5 million undergraduates in the United States.

Additionally, traditionally underserved students are disproportionately likely to encounter developmental math as a stumbling block on the road to college completion. The community college student population is more racially diverse, older, and lower income than 4-year university students (Bueschel, 2004). Minority students are placed in more developmental math courses and less likely to complete these courses to achieve college-level math credit than white students (Bailey et al., 2010; Chen, 2016). Improving the success rates of students in developmental math sequences is a key lever for advancing an equity agenda.

Several aspects of traditional developmental math sequences have been proposed as contributors to negative student outcomes. Traditionally, students must take long multi-course sequences of increasing levels of difficulty to fulfill developmental math requirements. A sequence of multiple developmental courses, such as basic arithmetic, pre-algebra, elementary algebra, and then intermediate algebra, leads into a college-level transferable class such as pre-calculus. This structure drastically hinders student completion. Even when students complete one course in a sequence, many fail to enroll in subsequent courses (Cullinane & Treisman, 2010; Bailey et al., 2010).

Additionally, the instruction in many math classrooms does not incorporate research-based curriculum design and pedagogic practices that foster deeper student learning and engagement (Mesa, 2011). Traditional math courses emphasize transmission of content over a more participatory approach (Edwards, Sandoval, & McNamara, 2015), factual and procedural knowledge over conceptual knowledge (Mesa, 2011), and do not demonstrate the relevancy of mathematical concepts (Carnevale & Desrochers, 2003). Furthermore, traditional developmental math courses do not address either language and literacy or non-cognitive barriers (e.g., math anxiety and stereotype threat) that impede many students' ability to learn math (Blackwell, Trzesniewski, & Dweck, 2007; Haynes, Perry, Stupnisky, & Daniels, 2009; Gomez, Rodela, Lozano, & Mancevice, 2013). More recently, the relevancy of the algebra-heavy content of traditional math curriculum has also been called to question. A study on the Survey of Workplace Skills, Technology, and Management Practices found that only 19% of employees use any algebra in their work (Handel, 2007).

To spur progress on this problem, Carnegie Foundation for the Advancement of Teaching convened a networked improvement community (NIC) - a national community of community college administrators and faculty, and educational researchers (Bryk, Gomez, Grunow, & LeMahieu, 2015). Through an improvement science approach, the NIC redesigned the content, pedagogy, and structure of traditional math sequences to increase the number of students completing their math requirements. The result of this work was two accelerated alternatives to traditional developmental math sequences for non-STEM students: Statway and Quantway. Statway is an accelerated year-long introductory college-level statistics course that integrates developmental math content. A previous study demonstrated Statway's efficacy and impact on student success over traditional developmental math programs (Yamada & Bryk, 2016).

Quantway provides another alternative to the traditional math sequence focusing on quantitative reasoning. As shown in Figure 1, Quantway 1 is a one-term quantitative reasoning course for students who place two levels below college-level, thus enabling them to complete their developmental math requirements in a single term. Students who successfully complete Quantway 1 are prepared for college level math and eligible to enroll in Quantway 2[1] or another college-level quantitative reasoning course.

Since the Quantway 1's launch in 2012, Quantway 1's implementation has grown more rapidly than Statway, with Quantway 1 enrollment growing from 418 to 1936 students over the first four years of implementation (Huang, Hoang, Yesilyurt, & Thorn, 2016). Because Quantway 1 fulfills developmental math requirements in one term, community colleges can easily integrate it into their current developmental math offerings. Quantway 1 has been successful in promoting student success in developmental math courses, essentially doubling the success rates of traditional developmental math courses in half the time. Notably, Quantway 1 maintained these high success rates even as student enrollment more than quadrupled. In the most recent 2014-2015 academic year, 57% of the students enrolled in Quantway 1 successfully completed the course in one term. In comparison, only 21% of a baseline group of developmental math students completed the traditional developmental math course in one year[2] (Huang et al., 2016).

---

[1] Five institutions have implemented Quantway 2, serving a total of 429 students over 3 years of implementation (Huang et al., 2016). For the purposes of this study, we evaluated the efficacy of Quantway 1.

[2] To compute this baseline success rate, we worked with institutional researchers from six of the first Quantway colleges. Analyses revealed that only 20.6 percent of students were able to successfully complete their

Despite these promising results, it is unclear whether Quantway 1's demonstrated impact is attributable to the program itself, or is due to differences in the students that select or are placed into Quantway 1. Building upon our descriptive results, this study pursues a more rigorous causal analysis of Quantway 1 through a propensity score technique, separating the program's effect from potential selection bias. These results would provide a stronger evidentiary base on which to base decisions about adopting and scaling Quantway 1.

## DESIGN OF QUANTWAY

Quantway 1 is designed around the premise that all students are capable of learning ambitious mathematics and succeeding in developmental math courses with the right supports. As summarized in Figure 2, Quantway 1 shares a working theory of improvement with its sister program Statway, aiming to increase student success through working on six key drivers: (1) acceleration of developmental math requirements, (2) implementation of a research-based instructional system, (3) socioemotional supports, (4) language and literacy supports, (5) faculty development, and (6) participation in a NIC (for more information on the theory of improvement, see Yamada & Bryk, 2016).

The way Quantway 1 addresses these drivers differs from that of Statway in order to fill a different niche in community college math departments and meet the needs of specific students. Below, we will elaborate on the features that distinguish Quantway 1 from other accelerated developmental math programs.

First, Quantway 1 accelerates students' ability to complete developmental math, getting them to college level math more quickly. Quantway 1 focuses on quantitative literacy, which is described as "the ability to adequately use elementary mathematical tools to interpret and manipulate quantitative data and ideas that arise in an individual's private, civic, and work life" (Gillman, 2004, p. 5). These quantitative literacy concepts are codified in a set of rigorous learning outcomes that were collaboratively established and vetted by a committee that included representatives from several mathematical professional societies.[3] Because Quantway 1's learning outcomes provide students with a strong foundation in numerical and quantitative reasoning concepts, it has served as preparatory quantitative reasoning course for many non-STEM pathways and majors and as the culminating math course for technical certificate programs. Some colleges offer Quantway as a pathway through college level math by combining Quantway 1 with Quantway 2 or another college level quantitative reasoning course. Quantway's flexible design can be easily integrated into current institutional structures and meets a variety of community college needs.

---

developmental math sequence within a full year. Additionally, 28.5 percent achieved this goal after two years, 31.6 percent after three years, and 33.3 percent after four years. For more information, see Huang et al., 2016.

[3] These mathematical societies include the National Numeracy Network, American Mathematics Association of Two-Year Colleges, and the Mathematical Association of America.

Second, Quantway 1's instructional system is designed to ground unfamiliar math concepts in familiar situations through contextualization. Quantway 1's lessons use authentic, relevant contexts and real data to increase student motivation to learn. Quantway 1 is organized around three intentional themes (citizenship, healthcare, and financial literacy) that reflect everyday concepts and are critically important in engaging in society. By illustrating the real world applications of math concepts, Quantway 1 can contribute previously unsuccessful students can have meaningful and positive interactions with quantitative reasoning content.

Like Statway, the Quantway 1 instructional system is designed to foster robust and sustained mathematical learning, emphasizing the teaching of concepts to improve both procedural and conceptual understanding (Hiebert & Grouws, 2007). The Quantway 1 instructional model is organized around three research-based learning opportunities – productive struggle, explicit connections, and deliberate practice. In productive struggle, faculty engage students in substantive mathematical tasks that encourage students to struggle with key mathematical concepts and solve problems that are challenging but still within reach (Hiebert & Grouws, 2007). By productively struggling, students can make meaning of the mathematical content for themselves and develop strategies for engaging with the content. Explicit connections refer to instruction that creates opportunities for students to make connections between mathematical procedures and underlying conceptual knowledge. Deliberate practice aims to improve student performance through a series of highly structured, increasingly sophisticated, and challenging tasks that deepen facility with key concepts (Edwards & Beattie, 2015). These learning opportunities are supported by instructional practices that facilitate student discussion and support collaborative learning around rich mathematical problems (Edwards & Beattie, 2015; Edwards et al., 2015).

Third, Quantway 1 integrates two types of research-based student supports designed to meet the needs of diverse student learners – productive persistence, and language and literacy supports. One set of supports is designed to promote students' ability to productively persist through rigorous math coursework. The socioemotional intervention, which we call Productive Persistence, consists of a collection of student activities and faculty actions that address the high-leverage non-cognitive factors that promote student tenacity and effective learning strategies (Edwards & Beattie, 2016). NIC members worked together with social psychologists to iteratively develop this *package* of productive persistence routines, interventions, and practices that work to promote growth mindset, reduce math anxiety, and increase students' sense of belonging. A second set of interventions is designed to support students in successfully grappling with the complex language and literacy demands of mathematics, with its different forms of representation and elaborate grammatical forms. Quantway 1 lessons embed language and literacy tools to support the comprehension and organization of information in quantitative situations. These lessons are written to avoid literacy barriers that developmental math students commonly face (Gomez, Rodela, Lozano, & Mancevice, 2013; Gomez et al., 2015).

Fourth, because the Quantway 1 curriculum and pedagogy significantly differ from traditional methods of teaching, Quantway 1 faculty are invited to participate in a comprehensive professional development program (Edwards et al., 2015). This Faculty Support Program prepares faculty to teach Quantway 1 and supports them in their first year of teaching, and provides ongoing opportunities for instructional improvement and professional learning. Through online resources, faculty mentorship, and ongoing workshops, this program prepares faculty to effectively implement Pathways' collaborative instructional approach, learning opportunities, and productive persistence and language and literacy supports.

Fifth, Quantway 1 faculty and administrators participate in a network improvement community (NIC) that provides them with a collaborative learning community to support them in teaching and implementing Quantway 1. The NIC social structure supports community colleges faculty and administrators in collectively generating and disseminating practical learning about what works, for whom, and under what conditions to reliably deliver efficacy at scale (Bryk et al., 2015).

Both Quantway 1 students and faculty report that the combination of these design elements creates a meaningfully different math experience from traditional developmental math courses. In addition, the success rates of Quantway 1 students in the first four years of implementation are significantly higher than institutional baselines at each of the participating colleges (Huang et al., 2016). However, evaluating the effectiveness of the Quantway 1 program requires comparing Quantway 1 student success to a reasonable counterfactual that represents how similar students would have performed if they had not taken Quantway 1. In this study, we used a propensity score matching technique (Rosenbaum & Rubin, 1983) to compare Quantway 1 students with similar students in traditional developmental math programs in the same institution. We conducted the propensity score analysis within a hierarchical linear modeling framework (Raudenbush & Bryk, 2002) to account for the nested structure of the data with students within institutions in the network. We conducted a follow-up sensitivity analysis to examine whether the effects could be explained by other unmeasured differences between the two groups of students.

We also looked at variation in performance across students, classrooms and institutions. In contrast to typical evaluations that report only the average impact of an intervention, this study assessed whether Quantway 1 is effective across the range of classrooms and institutions in the NIC. These investigations into variation support the program's ability to scale with efficacy (Bryk et al., 2015) and can inform where improvement efforts should be targeted in order to further increase success rates. We also examined possible differential effects of Quantway 1 across sex and race/ethnicity subgroups to determine the potential of the program to promote an equity agenda by improving outcomes across all race/ethnicity and sex subgroups.

## METHODS

### PARTICIPANTS

Quantway 1 was first implemented during the spring of 2012.[4] The initial cohort of students spanned 8 community colleges across three states (Georgia, New York, and Ohio). Throughout the 2014-15 academic year, Quantway 1 served 5561 students from a total of 14 colleges (see Appendix) across eight states (Georgia, Minnesota, New Jersey, New York, Ohio, Washington, West Virginia, and Wisconsin; Huang et al., 2016; Sowers & Yamada, 2015).

### DATA AND STUDY DESIGN

Institutional researchers from participating colleges provided background data on student characteristics, course enrollment and performance. The analytic sample of the current study consisted of 4,243 Quantway 1 students from 10 colleges who enrolled in a Quantway 1 course between the spring of 2012 and the fall of 2014, and 83,887 potential comparison group students from the corresponding semesters.

First, we identified a group of comparison traditional developmental math students with similar characteristics to Quantway 1 students. To obtain propensity scores, we took a hierarchical linear modeling (HLM) approach (Hong & Raudenbush, 2005, 2006; Raudenbush & Bryk, 2002; Yamada & Bryk, 2016) and constructed a two-level HLM model with a total of 37 student-level covariates including student background characteristics and prior course taking and success patterns during the two years prior to the Quantway 1 term. We selected covariates based on prior research findings and advice from institutional researchers in the participating colleges. The list includes standard student background data such as sex and race/ethnicity. It has been shown that these characteristics tend to differentiate students' progress in developmental math sequences (Bailey et al., 2010). We also matched on students' prior course-taking history and performance in the past two years. Previous research demonstrated that students' prior course taking history and success patterns are a more reliable indicator of students' educational and career goals than their declared program of study (Jenkins & Cho, 2012).

Table 1 presents all of the covariates used in the propensity score matching and their descriptive statistics before and after propensity score matching was conducted. We found a substantial number of unknown records for students' date of birth when computing students' age in years. To factor these cases into the propensity model, we constructed a dummy variable and coded missing age as 1, otherwise 0. Also, we accounted for six cohort groups by formulating a set of dummy variables with Spring 2014 as a reference category. The descriptive data on the left panel of Table 1 shows that overall Quantway 1 students have higher proportions of female and Hispanic students than the non-Quantway 1 students. Quantway 1 students had more course records in the two years before taking a Quantway 1 course,

[4] One college was on a quarter system until the fall of 2012 and implemented Quantway 1 for the first time in the winter of 2012.

suggesting that the term they took a Quantway 1 course was less likely to be their first semester or year. Quantway 1 students also started their developmental course(s) earlier, and attempted more developmental math courses and college-level courses than non-Quantway 1 students.

We conducted propensity score matching separately for each cohort and college by applying a nearest neighbor matching algorithm (Rosenbaum & Rubin, 1985). This algorithm was appropriate for our study because we wanted to retain as many Quantway 1 students as possible and had a large pool of non-Quantway 1 students for creating matches. We attempted to find up to five matches per Quantway 1 student (5:1 ratio matching) to maximize the best matches from the non-Quantway 1 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). For propensity score matching, we used the package MatchIt (Ho, Imai, King, & Stuart, 2011) in R (R Core Team, 2015).

We then estimated Quantway 1's effectiveness by comparing success rates of Quantway 1 students with their matched comparisons using a four-level HLM model with a binary outcome. Success was defined as a passing grade or a grade of C or higher[5] on a Quantway 1 course for Quantway 1 students and a developmental math course one level below college level (or another course deemed equivalent to a Quantway 1 course by faculty) for the matched comparison students. For the latter group, we tracked course outcomes over the entire academic year (i.e., tracking course outcomes over the fall and spring semesters for the fall cohorts and the spring, summer, and fall semesters for the spring cohorts). As described earlier, Quantway 1 accelerates traditional developmental math sequences for students placed two levels below college mathematics in one semester. Similar students following the traditional developmental math route typically complete the developmental sequence in one and a half years (Bailey et al., 2010; Cullinane & Treisman, 2010). Accordingly, if comparison students in the fall cohorts had failed a developmental math course one level below college level in the fall semester but passed it the following spring semester, we counted it as success. Therefore, analysis was conservative, providing comparison students twice as much time to reach the same success benchmark as Quantway 1 students.

In this HLM framework, matched clusters (level 1) were nested within Quantway 1 students (level 2), who were in turn nested within Quantway 1 faculty member classrooms (level 3) within their colleges (level 4). Because matched comparisons were constructed for each Quantway 1 student, their respective comparison students were also assigned the corresponding Quantway 1 faculty ID. This strategy allowed us to form each faculty member's classroom as a mini-experiment in which the mean outcome of their Quantway 1 students was compared with that of similar students who pursued traditional math courses, in order to

[5] A grade of C- or higher was used for a college that employed a +/– grading scheme.

estimate the variability in effect among faculty within colleges. We used HLM 7 (Raudenbush, Bryk, Cheong, Congdon, & du Toit, 2011) for all of the HLM analyses.

## RESULTS

### PROPENSITY SCORE MATCHING

To obtain propensity scores, we constructed a two-level Bernoulli model and estimated its model parameters using maximum likelihood via penalized quasi-likelihood estimation. $\phi_{il}$ is the probability of student *i* enrolling in Quantway 1 in college *l*. Accordingly, $\eta_{il}$ is the log-odds of this incident and formally expressed as:

**Level-1 Model (Student)**

$$\mathrm{Prob}(QW_{il}=1|\beta_l) = \phi_{il}$$
$$\log[\phi_{il}/(1 - \phi_{il})] = \eta_{il}$$
$$\eta_{il} = \beta_{0l} + \beta_{1l}(COV1_{il}) + \ldots + \beta_{37l}(COV37_{il}),$$

**Level-2 Model (College)**

$$\beta_{0l} = \gamma_{00} + u_{0l},$$
$$\beta_{1l} = \gamma_{10},$$
$$\vdots$$
$$B_{37l} = \gamma_{370},$$

where QW is a dummy variable indicating whether a given student was enrolled in Quantway 1 (coded as 1) or not (coded as 0), COV1…COV37 are the set of propensity score covariates.[6] We matched a total of 12,448 comparison students to 3,992 Quantway 1 students. Table 1 compares the descriptive statistics on each covariate before and after matching to the Quantway 1 group. Table 2 documents the balance in propensity score cohort by cohort for each college. There were no significant differences in mean propensity scores between the Quantway 1 and matched comparison students in any of the cohorts for each college (see *t* values). These results provide strong evidence that comparability of the groups was achieved on the measured covariates.

It may be worthwhile here to mention the matched ratios we accomplished. As described earlier in the Method section, we attempted to find up to five matches per Quantway 1 student. The matched ratios in the far right column suggest that in general, we identified 4 to 5

[6] We initially included two covariates of college non-STEM courses (the number of courses attempted and the respective success rate). However, they involved collinearity with other covariates, and accordingly, the model did not converge. Thus, we excluded them from the propensity model.

matches per Quantway 1 student. For some cohorts from Colleges 3 and 8, however, we identified fewer matches and needed to exclude some Quantway 1 students to maintain the comparability of the groups. It appears that both colleges have a relatively large population of students who were placed into developmental math courses and accordingly, more students at varying levels of developmental math. Therefore, it may be possible that certain kinds of students (e.g., those who failed developmental courses multiple times) were advised to take Quantway 1 so as to limit the number of appropriate students for matching.

**ESTIMATING QUANTWAY EFFECTS**

To estimate differences in success rates, we constructed a four-level Bernoulli model and estimated its model parameters using maximum likelihood via penalized quasi-likelihood estimation. $\phi_{ijkl}$ represents the probability that student *i* matched with Quantway 1 student *j* associated with faculty member *k*'s class in college *l* successfully completed the developmental math sequence. Correspondingly, $\eta_{ijkl}$ is the corresponding log-odds of this outcome and formally expressed as:

**Level 1 Model (Student)**

$$\mathrm{Prob}(SUCC_{ijkl}=1|\pi_{jkl}) = \phi_{ijkl},$$
$$\log[\phi_{ijkl}/(1 - \phi_{ijkl})] = \eta_{ijkl},$$
$$\eta_{ijkl} = \pi_{0jkl} + \pi_{1jkl}*(QW_{ijkl}) \ ,$$

**Level 2 Model (QW Student)**

$$\pi_{0jkl} = \beta_{00kl} + \beta_{01kl}(TERM_{jkl}) + \beta_{02kl}(W12_{jkl}) + \beta_{03kl}(S12_{jkl}) + \beta_{04kl}(F12_{jkl}) + \beta_{05kl}(S13_{jkl}) + \beta_{06kl}(F13_{jkl}) + \beta_{07kl}(F14_{jkl}) + r_{0jkl},$$
$$\pi_{1jkl} = \beta_{10kl} + \beta_{11kl}(TERM_{jkl}) + r_{1jkl} \ ,$$

**Level 3 Model (Faculty)**

$$\beta_{00kl} = \gamma_{000l} + u_{00kl},$$
$$\beta_{01kl} = \gamma_{010l},$$
$$\beta_{02kl} = \gamma_{020l},$$
$$\beta_{03kl} = \gamma_{030l},$$
$$\beta_{04kl} = \gamma_{040l},$$
$$\beta_{05kl} = \gamma_{050l},$$
$$\beta_{06kl} = \gamma_{060l},$$
$$\beta_{07kl} = \gamma_{070l},$$
$$\beta_{10kl} = \gamma_{100l} + u_{10kl},$$
$$\beta_{11kl} = \gamma_{110l},$$

**Level 4 Model (College)**

$$
\begin{aligned}
\gamma_{000l} &= \delta_{0000} + v_{000l} \\
\gamma_{010l} &= \delta_{0100}, \\
\gamma_{020l} &= \delta_{0200}, \\
\gamma_{030l} &= \delta_{0300}, \\
\gamma_{040l} &= \delta_{0400}, \\
\gamma_{050l} &= \delta_{0500}, \\
\gamma_{060l} &= \delta_{0600}, \\
\gamma_{070l} &= \delta_{0700}, \\
\gamma_{100l} &= \delta_{1000} + v_{100l}, \\
\gamma_{110l} &= \delta_{1100},
\end{aligned}
$$

where *SUCC* represents developmental math achievement (1 for successfully completed and 0 for not successfully completed), and *QW* is a dummy variable indicating whether the student was enrolled in Quantway 1 (coded as 1) or one of the matched comparisons (coded as 0). All the covariates at Level 2 were included as additional adjustment variables for the outcome. *Term* is a dummy variable indicating whether the outcome for matched comparison students was based on one semester (coded as 1) or the entire academic year (coded as 0). *W12* to *F14* are dummy variables for the six cohort groups described earlier in the Method section.[7] The results presented in Table 3 indicate that on average, Quantway 1 students demonstrated significantly higher odds of success, 2.05 (95% CI [1.33, 3.18][8]), in successfully completing the developmental math course than the matched comparison students. The corresponding estimated probabilities of success were 56.50% for the Quantway 1 group and 38.74% for the matched comparison group.

**VARIATION IN PERFORMANCE**

The estimated coefficients between the intercept and the slope at both college and faculty levels were negative (-.70 and -.41, respectively), suggesting that the lower the outcome for the matched comparison group, the larger the effect of Quantway 1. This inverse relationship was stronger at the college level.

In addition, we found variation in Quantway 1 effect among colleges and faculty members (0.35 and 0.20 for the college and faculty variances). Figures 3 and 4 display the variation in Quantway 1 effect size at the college and faculty levels, respectively. In both charts, we added three lines as references. The center line represents the average effect of Quantway 1, and the upper and lower lines represent the upper and lower bounds of the average effect (which are deviated in two *SE*s from the center line). Figure 3 demonstrates that there were positive Quantway 1 effects on student outcomes in all but College 10 (which showed no effect of

[7] We also constructed the same four-level model with individual students' propensity scores included in the level 1 model and those six cohort group variables added to the level 2 model for the slope. The results from this model revealed no significant coefficients of these additional covariates and closely mirrored those from the simpler model. For the ease of interpretation, we focus here on the results from the simpler model.

[8] HLM 7 generates 95% confidence intervals of odds ratios.

Quantway 1). College 8 stands out as a positive deviant with a Quantway 1 effect outside the upper bound of the average effect. Figure 4 shows the variation in Quantway 1 effectiveness across the classrooms in the NIC. The vast majority of Quantway 1 faculty at College 8 drastically outperformed the average Quantway 1 faculty, suggesting internal coherence at this institution. In contrast, a wide range of variation was observed among faculty members at College 3. Understanding the mechanisms that enable consistently high performance and investigating the causes of variation are areas of future study.

**SUBGROUP ANALYSIS**

To examine possible differential effects of Quantway 1 by sex and race/ethnicity subgroups, we constructed a four-level HLM similar to those described above. In this subgroup analysis, however, we applied effect coding to the grouping variables in order to directly represent both main and interaction effects on the outcome. The reference categories were female and White. Each of these was coded as -1. We excluded cases with the unknown sex status. Figure 5 presents the model-based results transformed back into their natural metrics of proportion of students successfully completing a developmental math sequence. This metric transformation was made for the ease of interpretation. Positive effects of Quantway 1 were observed for each race/ethnicity group. Black and Hispanic male students that take Quantway 1 exhibited the largest increase in completion rates relative to baseline levels of performance.

**SENSITIVITY ANALYSIS**

In general, Quantway 1 effects were strong and prevalent for all subgroups. The validity of these effects was based on an assumption of a 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 Quantway 1 effects to possible confounding by unmeasured variables (Hong & Raudenbush, 2005, 2006; Lin, Psaty, & Kronmal, 1998). Given some unmeasured covariates (U), the Quantway 1 effect ($\delta$) can be re-estimated by adjusting for hypothesized hidden bias ($\gamma(E[U_1]-E[U_0])$) as $\delta^* = \delta - \gamma(E[U_1]-E[U_0])$, where $\gamma$ is the unmeasured covariates' association with the outcome and $E[U_1]-E[U_0]$ is their association with treatment assignment (i.e., Quantway or non-Quantway enrollment).

Adapting the approach of Hong and Raudenbush (2005, 2006), we operationally defined a proxy for $\gamma$ as a coefficient derived from a four-level model designed to predict the outcome with the same set of covariates used in the propensity score analysis and $E[U_1]-E[U_0]$ as the observed mean difference between the Quantway and non-Quantway groups on the corresponding covariate. We then selected the largest positive value of the product of these two values as the largest possible bias[9] and obtained an adjusted Quantway estimate ($\delta^*$).

[9] We used the sum of the product values for those requiring a set of dummy variables (e.g., cohort group, race/ethnicity).

Accordingly, we re-estimated a Quantway 1 effect on the outcome and constructed a 95% confidence interval for the adjusted estimate. The adjusted estimate was .67 in logits (95% CIs [.26, 1.08]), and the corresponding confidence interval did not contain 0 or any negative value, thereby supporting the strong ignorability assumption. Our sensitivity analysis concludes that it is very unlikely that our general conclusion regarding Quantway 1's positive effects was influenced by the omission of unmeasured confounding factors.

## DISCUSSION

This study assessed Quantway 1's effectiveness for community college students across six semesters of implementation using a rigorous causal analysis. A propensity score matching technique (Rosenbaum & Rubin, 1983) within an HLM framework (Raudenbush & Bryk, 2002) allowed us to control for possible selection bias by matching Quantway 1 students with comparable students enrolled in traditional developmental math sequences across 37 student characteristics. We also undertook a sensitivity analysis to examine the possibility that the estimated effects were influenced by unmeasured confounding variables. Throughout these analyses, Quantway 1 students demonstrated significantly higher odds of success than matched comparison students. Our analyses also indicated that these results were not due to unmeasured differences between the two groups. We conclude that Quantway 1 substantially improves student success rates in fulfilling developmental math course requirements.

While typical evaluations may stop at estimating the effect size of Quantway 1, this study also sought to understand the variation of the Quantway 1 program across different colleges, faculty, and student subgroups. In order to achieve efficacy at scale, Quantway 1 must not only produce a positive effect on average, but must also be effective for diverse student populations across a range of different classroom and institutional contexts. Our analysis found that Quantway 1 effects were positive across all sex and racial/ethnic subgroups of students. As previously stated, students from traditionally underserved groups, including Blacks, Hispanics, and low-income students, are more likely to participate in developmental math courses (Chen 2016). Because ineffective traditional developmental math courses have a disproportionate impact on these traditionally underserved groups, these results suggest that Quantway 1 can play an important role in increasing the overall number of traditionally underserved students completing their math requirements. In addition, Quantway 1 has a positive effect in nearly all classrooms and colleges in the network, indicating that the program can work for varied faculty in different institutional contexts.

Quantway 1's design includes key levers that may explain why it better supports traditionally underserved community college students. First, Quantway 1 is a quantitative literacy course that accelerates student progress to college-level math by offering developmental math requirements in a single term. Second, Quantway 1's research-based instructional system contextualizes math concepts and is organized around three learning opportunities to promote rich mathematical learning for a broader range of students. Anecdotal accounts from students indicate that Quantway 1's unique mathematical experiences help them see themselves as mathematical learners and doers. Third, Quantway 1 aims to support socioemotional skills and provide language and literacy supports to help students grapple with the complex language of mathematics. Finally, Quantway 1's Faculty Support Program and the NIC structure support faculty in implementing Quantway 1's unique pedagogical practices across different faculty and institutional contexts.

Our results suggest that Quantway 1's comprehensive and systematic approach to tackling the typical barriers that developmental math students face is key to its success. Further empirical evidence is needed to connect particular design elements to the positive effects of the program. For now, we can conclude that the Quantway 1 package is an effective alternative to the traditional developmental math sequence and accelerates the ability of a diverse range of students to complete their developmental math requirements in a variety of contexts. These results and Quantway 1's flexible single-term structure demonstrate its significant potential to positively impact numerous students in a variety of community college contexts.

It is worth noting a couple of the key limitations of the current study that would be fruitful topics for future investigations. One opportunity for future research is to track college-level math achievement between the two matched groups one year after Quantway 1 enrollment to determine if Quantway 1 students perform comparably or better than matched student groups in future college-level math courses. Since Quantway 1 is designed to not only get students through their developmental math sequences but to prepare them to meet their college math requirements, this will be a particularly important analysis in determining Quantway 1's effectiveness. As longitudinal data become available, we also plan to track longer-term outcomes, such as transfer rates and academic success of Quantway 1 students in 4 year institutions.

The significant variation in outcomes across faculty and colleges demonstrated in Figures 3 and 4 presents another opportunity for further investigation. The goal of quality improvement is to reduce the variation between classrooms and colleges achieving positive results across diverse contexts. Investigating positive and negative deviants provides insight into the key sources of variation. College 8, for example, significantly outperforms the other colleges in the network and maintains high performance across all the classrooms in the college. College 10, in contrast, performs significantly worse than other colleges. Future research should explore whether these colleges differ in how they enact the key design elements described above, and study the various adaptations that these colleges made in response to their local context. Discovering and sharing key practices across NIC colleges would enhance the network's ability to replicate Quantway 1's positive outcomes as it spreads to more diverse contexts.

In conclusion, by redesigning the content, pedagogy, and structure of traditional developmental math courses, Quantway 1 provides a rich mathematical experience for a broader range of developmental students, including historically underserved groups. These efforts have contributed to Quantway 1's positive impact on equitable outcomes by improving completion rates for all sex and racial/ethnic subgroups and across diverse contexts. Despite great advances in increasing developmental math completion rates on average, variation in outcomes across faculty and colleges in the NIC indicates there is still much work to be done in advancing Quantway 1's efficacy reliably at scale. By leveraging the NIC structure, we will continue to accelerate learning through quality improvement to solve this developmental math crisis.

## 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.

Blackwell, L. S., Trzesniewski, K. H., & Dweck, C. S. (2007). Implicit theories of intelligence predict achievement across an adolescent transition: A longitudinal study and an intervention. *Child Development*, *78*, 246–263.

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.

Bueschel, A. C. (2004). The missing link: The role of community colleges in the transition between high school and college. In M. W. Kirst and A. Venezia (Eds.), *From high school to college: Improving opportunities for success in postsecondary education* (pp. 252–284). San Francisco: Jossey-Bass.

Carnevale, A. P., & Desrochers, D. M. (2003). *Standards for what?: The economic roots of K-16 reform*. Princeton, NJ: Educational Testing Service.

Carnevale, A. P., Smith, N., & Strohl, J. (2013). *Recovery: Projections of jobs and education requirements through 2020*. Georgetown University Center on Education and the Workforce.

Chen, X. (2016). *Remedial coursetaking at U.S. public 2- and 4-year institutions: Scope, experiences, and outcomes* (NCES 2016-405). U.S. Department of Education, Washinton, DC: National Center for Education Statistics.

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.

Edwards, A. & Beattie, R. (2015). Promoting student learning and productive persistence in developmental mathematics. *NADE Digest, 9*, 30-39.

Edwards, A. R., Sandoval, C., & McNamara, H. (2015). Designing for improvement in professional development for community college developmental mathematics faculty. *Journal of Teacher Education, 66,*466-481. doi: 10.1177/0022487115602313.

Gillman, R. (2004). SIGMAA is Formed. Focus, 24(1), 5.

Gomez, K., Rodela, K., Lozano, M., & Mancevice, N. (2013). Designing embedded language and literacy supports for developmental mathematics teaching and learning. *MathAMATYC Educator, 5,* 43-56.

Gomez, K., Gomez, L. M., Rodela, K. C., Horton, E. S., Cunningham, J., & Ambrocio, R. (2015). Embedding language support in developmental mathematics lessons: Exploring the value of design as professional development for community college mathematics instructors. *Journal of Teacher Education, 66,* 450-465. doi: 10.1177/ 0022487115602127.

Handel, M. J. (2007, May 31 – June 1). A new survey of workplace skills, technology, and management practices (STAMP): Background and descriptive statistics. Paper presented at the Workshop on Research Evidence Related to Future Skill Demands of the National Research Council of the National Academies, Washington, DC.

Haynes, T. L., Perry, R. P., Stupnisky, R. H., & Daniels, L. M. (2009). A review of attributional retraining treatments: Fostering engagement and persistence in vulnerable college students. In J. C. Smart (Ed.), *Higher education: Handbook of theory and research* (pp. 227–272). New York, NY: Springer.

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.

Ho, D. E., Imai, K., King, G., & Stuart, E. A. (2011). MatchIt: Nonparametric preprocessing for parametric causal inference. *Journal of Statistical Software, 42*, 1-28.

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.

Huang, M., Hoang, H., Yesilyurt, S., & Thorn, C. (2016). *Community College Pathways: 2014-2015 Impact Report*. Stanford, CA: Carnegie Foundation for the Advancement of Teaching.

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.

Johnstone, R. (2013). *Fiscal considerations of Statway® and Quantway®: We should be doing this anyway, but here's how it may help the bottom line*. National Center for Inquiry & Improvement (NCII). Retrieved from http://www.inquiry2improvement.com/attachments/article/12/NCII-Carnegie_SW-QW_Fiscal_Considerations_110713-Rob-NCII.pdf.

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.

Mesa, V. (2011). Similarities and differences in classroom interaction between remedial and college mathematics courses in a community college. *Journal on Excellence in College Teaching, 22*(4), 21-55.

R Core Team. (2015). *R: A language and environment for statistical computing [Computer software]*. Vienna, Austria: R Foundation for Statistical Computing.

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., & 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.

Sowers, N., & Yamada, H. (2015). *Pathways impact report*. Stanford, CA: Carnegie Foundation for the Advancement of Teaching.

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,* 179-204.

# APPENDIX

## List of Participating Colleges

- Atlantic Cape Community College
- Borough of Manhattan Community College
- Cuyahoga Community College
- East Georgia State College
- Madison College
- Marshall University
- Onondaga Community College
- Ridgewater College
- Rockland Community College
- Sinclair Community College
- South Georgia State College
- University of North Georgia, Gainesville
- University of Washington, Bothell
- Westchester Community College

**Table 1.**

**Descriptive Statistics of Covariates in the Two-Level Propensity Model**

| | Sample before matching | | Sample after matching | |
|---|---|---|---|---|
| | Non-Quantway 1 | Quantway 1 | Non-Quantway 1 | Quantway 1 |
| | % | % | % | % |
| Sex | | | | |
| Female* | 56 | 62 | 60 | 61 |
| Male | 44 | 37 | 39 | 38 |
| Unknown | 0 | 1 | 1 | 1 |
| Race/Ethnicity | | | | |
| Asian | 3 | 4 | 3 | 4 |
| Black | 31 | 30 | 32 | 30 |
| Hispanic | 18 | 26 | 21 | 26 |
| White* | 36 | 34 | 36 | 33 |
| Multiracial | 1 | 1 | 1 | 1 |
| Other | 1 | 0 | 0 | 0 |
| Unknown | 9 | 5 | 6 | 5 |
| Any course records in past two years | | | | |
| No* | 45 | 38 | 46 | 41 |
| Yes | 55 | 62 | 54 | 59 |
| Cohort group | | | | |
| Winter 2012 | 6 | 2 | 3 | 2 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Spring 2012 | 16 | | 11 | | 16 | | 11 | |
| Fall 2012 | 14 | | 13 | | 20 | | 13 | |
| Spring 2013 | 16 | | 20 | | 14 | | 20 | |
| Fall 2013 | 16 | | 21 | | 20 | | 21 | |
| Spring 2014* | 17 | | 15 | | 14 | | 15 | |
| Fall 2014 | 15 | | 19 | | 14 | | 19 | |
| Age missing | 21 | | 14 | | 23 | | 15 | |
| | *M* | *SD* | *M* | *SD* | *M* | *SD* | *M* | *SD* |
| Age (in years) | 24.98 | 8.47 | 24.09 | 8.18 | 24.09 | 7.55 | 23.97 | 8.11 |
| Semesters since first developmental math course | 0.92 | 1.70 | 1.62 | 2.46 | 1.27 | 2.12 | 1.37 | 2.25 |
| Course load | 3.69 | 1.20 | 3.95 | 1.14 | 3.95 | 1.19 | 3.93 | 1.14 |
| Developmental math | | | | | | | | |
| One level below college level | | | | | | | | |
| Number of courses attempted | 0.09 | 0.31 | 0.21 | 0.55 | 0.15 | 0.41 | 0.17 | 0.47 |
| Success rate | 0.00 | 0.04 | 0.00 | 0.04 | 0.00 | 0.04 | 0.00 | 0.03 |
| Two levels below college level | | | | | | | | |
| Number of courses attempted | 0.21 | 0.48 | 0.35 | 0.65 | 0.26 | 0.56 | 0.30 | 0.58 |
| Success rate | 0.11 | 0.31 | 0.19 | 0.38 | 0.13 | 0.33 | 0.17 | 0.36 |
| Three or more levels below college level | | | | | | | | |
| Number of courses attempted | 0.18 | 0.50 | 0.16 | 0.55 | 0.12 | 0.45 | 0.13 | 0.49 |
| Success rate | 0.10 | 0.29 | 0.08 | 0.27 | 0.07 | 0.25 | 0.07 | 0.25 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Developmental English | | | | | | | | |
| Number of courses attempted | 0.10 | 0.37 | 0.08 | 0.33 | 0.08 | 0.35 | 0.08 | 0.32 |
| Success rate | 0.06 | 0.24 | 0.05 | 0.21 | 0.05 | 0.21 | 0.05 | 0.21 |
| Developmental reading | | | | | | | | |
| Number of courses attempted | 0.07 | 0.28 | 0.11 | 0.38 | 0.09 | 0.32 | 0.11 | 0.37 |
| Success rate | 0.05 | 0.21 | 0.06 | 0.24 | 0.05 | 0.22 | 0.06 | 0.23 |
| Developmental writing | | | | | | | | |
| Number of courses attempted | 0.10 | 0.32 | 0.11 | 0.34 | 0.09 | 0.32 | 0.10 | 0.34 |
| Success rate | 0.07 | 0.25 | 0.07 | 0.26 | 0.06 | 0.24 | 0.07 | 0.26 |
| College math | | | | | | | | |
| Number of courses attempted | 0.03 | 0.18 | 0.08 | 0.29 | 0.05 | 0.27 | 0.07 | 0.28 |
| Success rate | 0.01 | 0.07 | 0.01 | 0.08 | 0.00 | 0.06 | 0.01 | 0.07 |
| College non-math | | | | | | | | |
| Number of courses attempted | 2.10 | 3.57 | 4.32 | 6.01 | 3.29 | 5.17 | 3.76 | 5.42 |
| Success rate | 0.33 | 0.42 | 0.42 | 0.42 | 0.35 | 0.42 | 0.40 | 0.42 |
| College STEM | | | | | | | | |
| Number of courses attempted | 0.30 | 1.11 | 0.49 | 1.30 | 0.44 | 1.48 | 0.45 | 1.25 |
| Success rate | 0.07 | 0.24 | 0.09 | 0.26 | 0.08 | 0.25 | 0.08 | 0.25 |

*Note*. Terms with "*" were used as reference categories (coded as 0) when formulating dummy variables. Age was computed in years using a date of birth and 9/1 for the fall cohorts and 3/1 for the spring cohorts (1/1 for one winter cohort group). In the current propensity model, we centered age around age 18. Semesters since first developmental math course takes an integer, such as 0, 1, 2, etc., where 0 means a student took a developmental math course for the first time in the same term as the Quantway 1 term, 1 one semester before, 2 two semesters before, and so on. Course load refers to the number of courses a student took during the Quantway 1 term. Success rate was computed by dividing the number of courses completed with a pass in a pass/fail grading scheme, or a C or higher (C- if a +/- grading scheme is used) by the number of courses attempted.

**Table 2.**

**Balance in Logit of the Propensity Score for non-Quantway 1 and Quantway 1 Students**

| | | Sample before matching | | | | | | Sample after matching | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Non-Quantway 1 | | | Quantway 1 | | | Non-Quantway 1 | | | Quantway 1 | | | | Matched |
| College | Cohort | *n* | *M* | *SD* | *n* | *M* | *SD* | *n* | *M* | *SD* | *n* | *M* | *SD* | *t* | ratio |
| 1 | 2012 Spring | 585 | -2.78 | 0.48 | 43 | -2.72 | 0.37 | 212 | -2.74 | 0.32 | 43 | -2.72 | 0.37 | -0.42 | 4.93 |
| 1 | 2012 Fall | 470 | -2.41 | 0.31 | 34 | -2.20 | 0.54 | 149 | -2.36 | 0.35 | 31 | -2.31 | 0.42 | -0.59 | 4.81 |
| 1 | 2013 Fall | 305 | -1.88 | 0.19 | 59 | -1.79 | 0.38 | 249 | -1.89 | 0.15 | 54 | -1.88 | 0.16 | -0.12 | 4.61 |
| 1 | 2014 Spring | 273 | -2.32 | 0.26 | 29 | -2.01 | 0.52 | 112 | -2.23 | 0.26 | 25 | -2.16 | 0.34 | -0.94 | 4.48 |
| 2 | 2013 Fall | 690 | -2.34 | 0.96 | 69 | -2.29 | 0.80 | 337 | -2.31 | 0.75 | 69 | -2.29 | 0.80 | -0.16 | 4.88 |
| 2 | 2014 Spring | 270 | -2.93 | 0.62 | 17 | -3.02 | 0.27 | 85 | -3.02 | 0.27 | 17 | -3.02 | 0.27 | -0.01 | 5.00 |
| 2 | 2014 Fall | 402 | -2.86 | 0.41 | 47 | -2.99 | 0.36 | 217 | -2.95 | 0.26 | 46 | -2.96 | 0.32 | 0.18 | 4.72 |
| 3 | 2012 Spring | 4138 | -3.38 | 0.39 | 72 | -3.37 | 0.27 | 360 | -3.37 | 0.27 | 72 | -3.37 | 0.27 | -0.05 | 5.00 |

| | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 3 | 2012 Fall | 3234 | -2.86 | 0.40 | 177 | -2.74 | 0.42 | 875 | -2.76 | 0.38 | 175 | -2.76 | 0.38 | -0.07 | 5.00 |
| 3 | 2013 Spring | 3745 | -2.24 | 0.43 | 584 | -1.93 | 0.75 | 1057 | -2.11 | 0.53 | 544 | -2.06 | 0.59 | -1.66 | 1.94 |
| 3 | 2013 Fall | 2358 | -2.11 | 0.51 | 408 | -1.66 | 0.93 | 739 | -1.89 | 0.64 | 378 | -1.84 | 0.72 | -1.28 | 1.96 |
| 3 | 2014 Spring | 3242 | -2.58 | 0.54 | 290 | -2.12 | 0.81 | 559 | -2.20 | 0.72 | 287 | -2.14 | 0.78 | -1.08 | 1.95 |
| 3 | 2014 Fall | 4696 | -2.46 | 0.36 | 402 | -1.90 | 0.94 | 368 | -2.08 | 0.69 | 368 | -2.07 | 0.71 | -0.16 | 1.00 |
| 4 | 2012 Spring | 594 | -3.20 | 0.66 | 38 | -2.78 | 1.27 | 175 | -3.03 | 0.88 | 36 | -2.97 | 0.97 | -0.33 | 4.86 |
| 4 | 2012 Fall | 570 | -2.88 | 0.47 | 45 | -2.40 | 0.83 | 193 | -2.67 | 0.48 | 42 | -2.54 | 0.65 | -1.22 | 4.60 |
| 4 | 2013 Spring | 599 | -2.20 | 0.48 | 42 | -1.91 | 0.73 | 188 | -2.09 | 0.50 | 41 | -1.96 | 0.68 | -1.18 | 4.59 |
| 4 | 2013 Fall | 681 | -2.33 | 0.46 | 69 | -2.01 | 0.89 | 278 | -2.28 | 0.48 | 63 | -2.20 | 0.66 | -0.84 | 4.41 |
| 4 | 2014 Spring | 617 | -2.78 | 0.50 | 49 | -2.43 | 0.81 | 213 | -2.65 | 0.57 | 47 | -2.51 | 0.72 | -1.16 | 4.53 |
| 4 | 2014 Fall | 827 | -2.66 | 0.38 | 87 | -2.48 | 0.72 | 408 | -2.63 | 0.41 | 85 | -2.56 | 0.53 | -1.17 | 4.80 |
| 5 | 2013 Fall | 712 | -3.88 | 0.58 | 6 | -3.60 | 0.76 | 30 | -3.61 | 0.68 | 6 | -3.60 | 0.76 | -0.02 | 5.00 |
| 5 | 2014 Spring | 648 | -4.58 | 0.58 | 19 | -3.65 | 0.93 | 82 | -3.88 | 0.76 | 19 | -3.65 | 0.93 | -0.99 | 4.32 |
| 6 | 2012 Spring | 1601 | -4.72 | 0.45 | 21 | -4.74 | 0.35 | 105 | -4.74 | 0.34 | 21 | -4.74 | 0.35 | -0.05 | 5.00 |
| 6 | 2013 Spring | 1481 | -3.75 | 0.55 | 35 | -3.44 | 0.87 | 167 | -3.57 | 0.63 | 34 | -3.52 | 0.73 | -0.34 | 4.91 |
| 6 | 2013 Fall | 1534 | -3.82 | 0.49 | 49 | -3.49 | 0.78 | 232 | -3.60 | 0.65 | 48 | -3.54 | 0.73 | -0.53 | 4.83 |
| 6 | 2014 Spring | 1436 | -4.20 | 0.45 | 32 | -3.76 | 0.87 | 140 | -3.88 | 0.55 | 29 | -3.83 | 0.58 | -0.41 | 4.83 |
| 6 | 2014 Fall | 1954 | -4.16 | 0.35 | 17 | -3.44 | 0.85 | 71 | -3.70 | 0.63 | 16 | -3.55 | 0.74 | -0.72 | 4.44 |
| 7 | 2012 Spring | 3675 | -4.79 | 0.91 | 63 | -4.49 | 1.02 | 305 | -4.53 | 0.99 | 62 | -4.49 | 1.03 | -0.08 | 4.92 |
| 7 | 2012 Fall | 2929 | -4.68 | 0.58 | 65 | -4.47 | 0.67 | 320 | -4.52 | 0.58 | 65 | -4.47 | 0.67 | -0.35 | 4.92 |
| 7 | 2013 Spring | 3831 | -4.05 | 0.49 | 42 | -3.92 | 0.52 | 204 | -3.97 | 0.45 | 42 | -3.92 | 0.52 | -0.08 | 4.86 |
| 7 | 2013 Fall | 3566 | -4.21 | 0.44 | 68 | -4.17 | 0.36 | 338 | -4.18 | 0.34 | 68 | -4.17 | 0.36 | -0.02 | 4.97 |

| | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 7 | 2014 Spring | 4097 | -4.65 | 0.45 | 29 | -4.29 | 0.80 | 127 | -4.54 | 0.47 | 27 | -4.41 | 0.70 | -1.11 | 4.70 |
| 8 | 2012 Winter | 4693 | -5.45 | 1.30 | 70 | -3.90 | 1.55 | 348 | -3.93 | 1.52 | 70 | -3.90 | 1.55 | -0.16 | 4.97 |
| 8 | 2012 Spring | 1955 | -4.39 | 0.91 | 108 | -2.32 | 1.83 | 275 | -2.91 | 1.22 | 97 | -2.72 | 1.36 | -1.23 | 2.84 |
| 8 | 2012 Fall | 3420 | -3.94 | 0.88 | 124 | -2.14 | 1.69 | 443 | -2.51 | 1.30 | 120 | -2.29 | 1.47 | -1.48 | 3.69 |
| 8 | 2013 Spring | 3615 | -3.36 | 0.60 | 129 | -1.93 | 1.36 | 119 | -2.13 | 1.17 | 119 | -2.10 | 1.20 | -0.19 | 1.00 |
| 8 | 2013 Fall | 3230 | -3.33 | 0.62 | 119 | -1.87 | 1.46 | 105 | -2.23 | 1.19 | 105 | -2.20 | 1.20 | -0.22 | 1.00 |
| 8 | 2014 Spring | 3088 | -3.79 | 0.52 | 118 | -2.49 | 1.23 | 165 | -3.16 | 0.74 | 88 | -3.04 | 0.83 | -1.10 | 1.88 |
| 8 | 2014 Fall | 3796 | -3.61 | 0.49 | 158 | -2.55 | 1.37 | 253 | -3.07 | 0.97 | 138 | -2.89 | 1.09 | -1.60 | 1.83 |
| 9 | 2012 Spring | 683 | -2.86 | 0.56 | 41 | -2.88 | 0.70 | 195 | -2.97 | 0.56 | 40 | -2.93 | 0.62 | -0.37 | 4.88 |
| 9 | 2012 Fall | 776 | -2.75 | 0.34 | 55 | -2.33 | 1.00 | 226 | -2.71 | 0.37 | 50 | -2.58 | 0.54 | -1.58 | 4.52 |
| 9 | 2014 Spring | 543 | -2.59 | 0.38 | 30 | -2.63 | 0.38 | 142 | -2.59 | 0.33 | 29 | -2.62 | 0.38 | 0.38 | 4.90 |
| 9 | 2014 Fall | 574 | -2.49 | 0.29 | 71 | -2.36 | 0.45 | 303 | -2.43 | 0.27 | 68 | -2.39 | 0.41 | -0.91 | 4.46 |
| 10 | 2012 Spring | 520 | -2.36 | 0.52 | 72 | -2.41 | 0.58 | 343 | -2.44 | 0.52 | 72 | -2.41 | 0.58 | -0.36 | 4.76 |
| 10 | 2012 Fall | 376 | -2.33 | 0.38 | 48 | -2.29 | 0.41 | 229 | -2.32 | 0.37 | 48 | -2.29 | 0.41 | -0.43 | 4.77 |
| 10 | 2013 Fall | 243 | -1.94 | 0.15 | 39 | -1.87 | 0.16 | 164 | -1.91 | 0.14 | 39 | -1.87 | 0.16 | -1.33 | 4.21 |
| 10 | 2014 Spring | 291 | -2.03 | 0.40 | 27 | -2.13 | 0.32 | 134 | -2.14 | 0.31 | 27 | -2.13 | 0.32 | -0.13 | 4.96 |
| 10 | 2014 Fall | 324 | -2.12 | 0.31 | 27 | -1.76 | 0.65 | 109 | -2.05 | 0.25 | 22 | -2.04 | 0.26 | -0.22 | 4.95 |

**Table 3.**

**Model-Based Estimation of Quantway 1 Effect on Developmental Math Achievement**

| Fixed effect | Coefficient | *SE* | *t* | *p* | Odds ratio |
|---|---|---|---|---|---|
| Intercept | -0.49 | 0.15 | -3.20 | .005 | 0.61 |
| Term | -0.71 | 0.14 | -5.24 | <.001 | 0.49 |
| W12 | 0.08 | 0.14 | 0.55 | .585 | 1.08 |
| S12 | 0.04 | 0.07 | 0.63 | .531 | 1.04 |
| F12 | -0.11 | 0.06 | -1.79 | .073 | 0.89 |
| S13 | -0.19 | 0.06 | -2.88 | .004 | 0.83 |
| F13 | 0.11 | 0.06 | 1.83 | .068 | 1.12 |
| F14 | 0.01 | 0.07 | 0.21 | .834 | 1.01 |
| Quantway 1 | 0.72 | 0.21 | 3.47 | .003 | 2.05 |
| Term | 0.30 | 0.30 | 1.00 | .317 | 1.35 |
| Random effect at level 4 (college) | Variance | *df* | $\chi^2$ | *p* | Correlation |
| Intercept | 0.22 | 9 | 311.84 | < .001 | -0.70 |
| Quantway 1 | 0.35 | 9 | 97.93 | < .001 | |
| Random effect at level 3 (faculty) | Variance | *df* | $\chi^2$ | *p* | Correlation |
| Intercept | 0.02 | 70 | 112.41 | .001 | -0.41 |
| Quantway 1 | 0.20 | 70 | 182.71 | < .001 | |

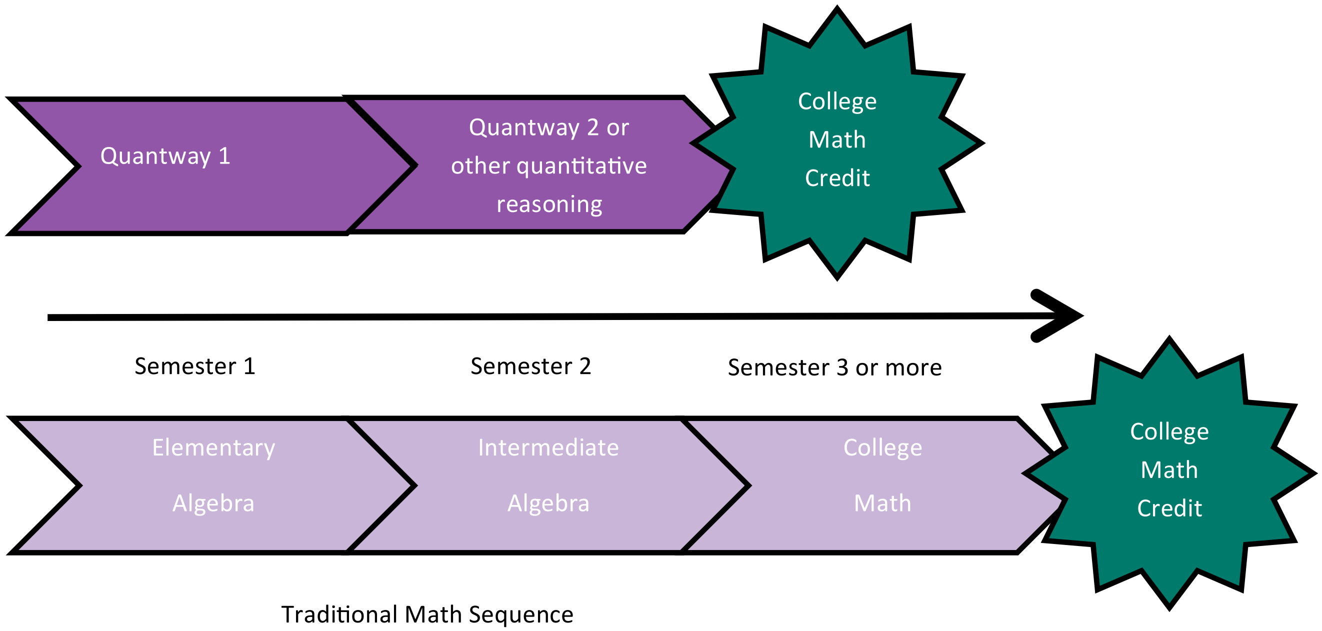


**Figure 1. Quantway 1 vs. Traditional math sequence**

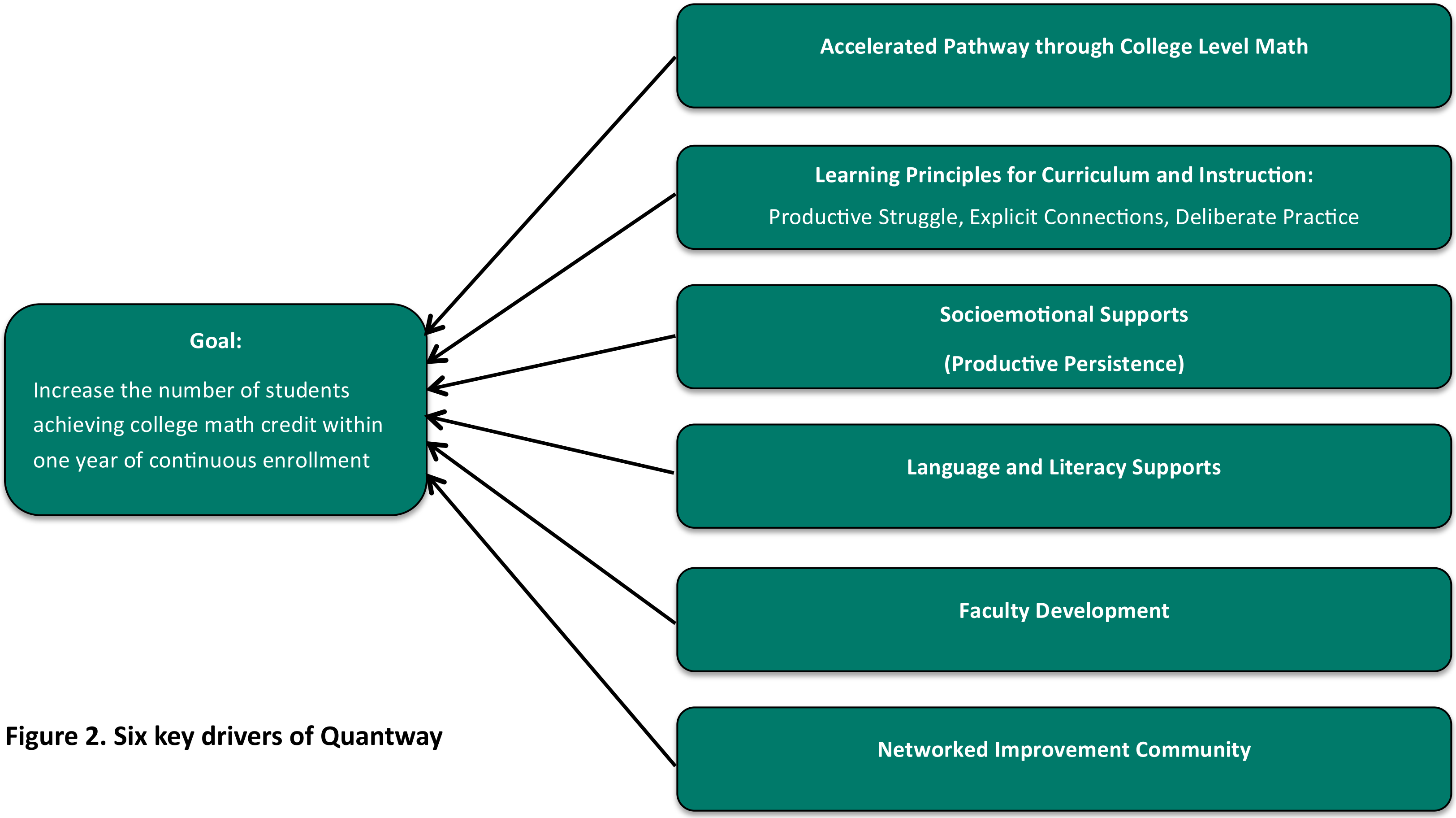


**Figure 2. Six key drivers of Quantway**

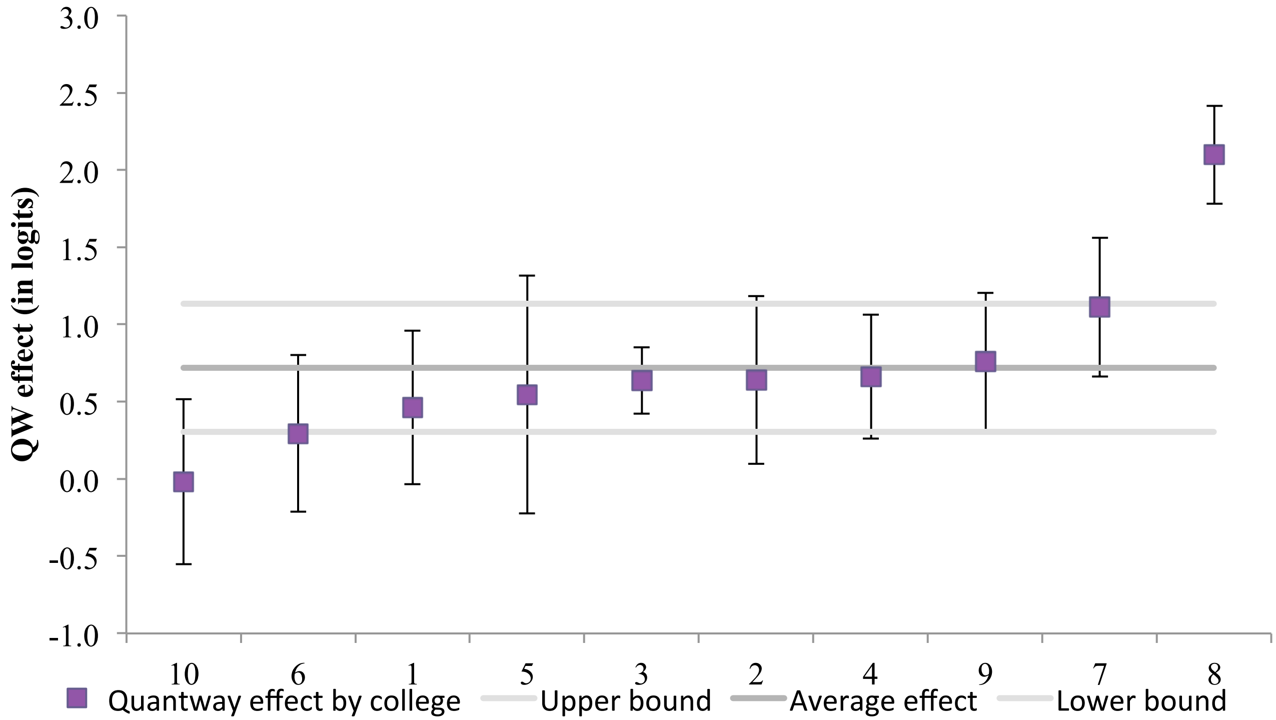


**Figure 3. Variation in Quantway 1 effect among colleges**

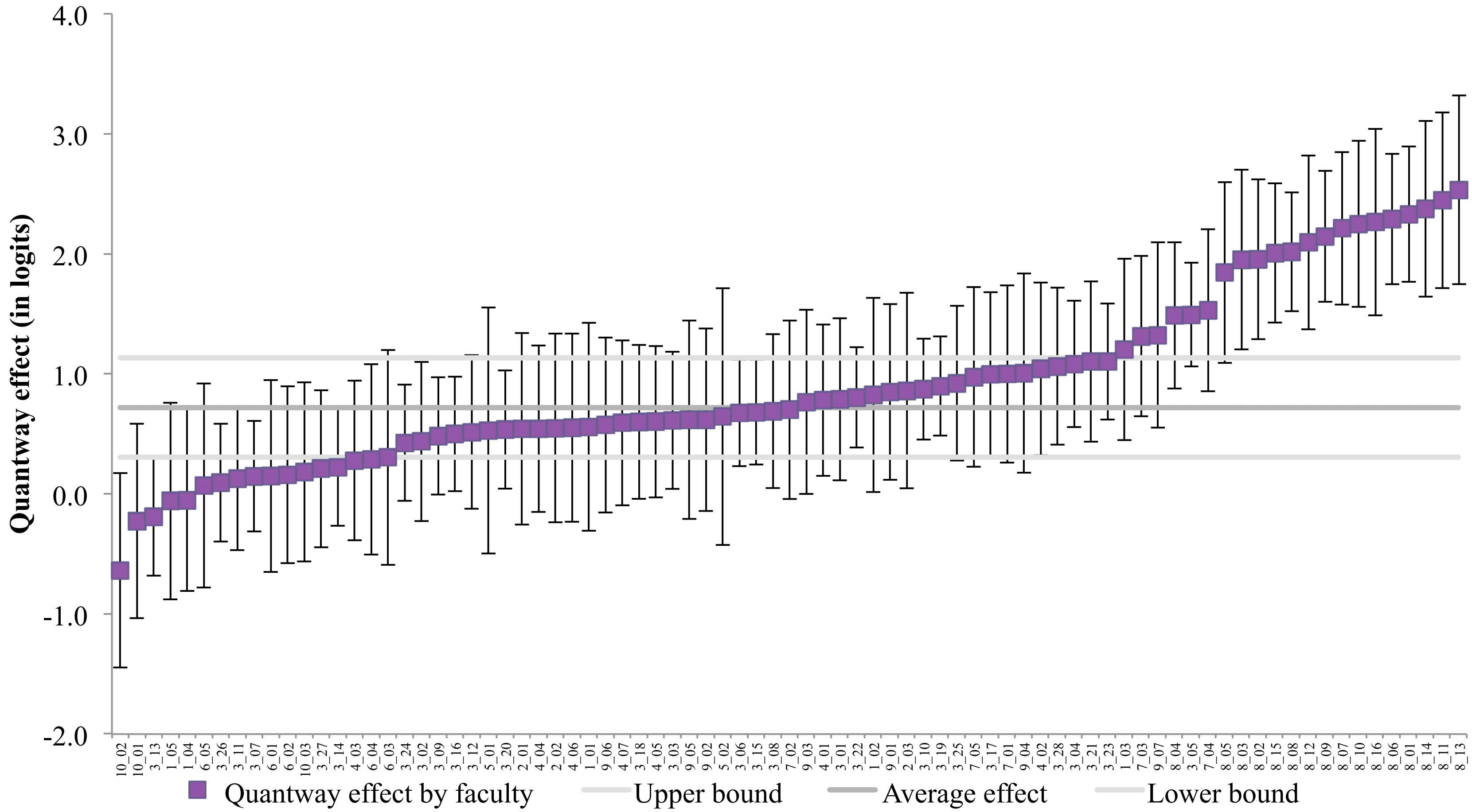


**Figure 4. Variation in Quantway 1 effect among faculty members**

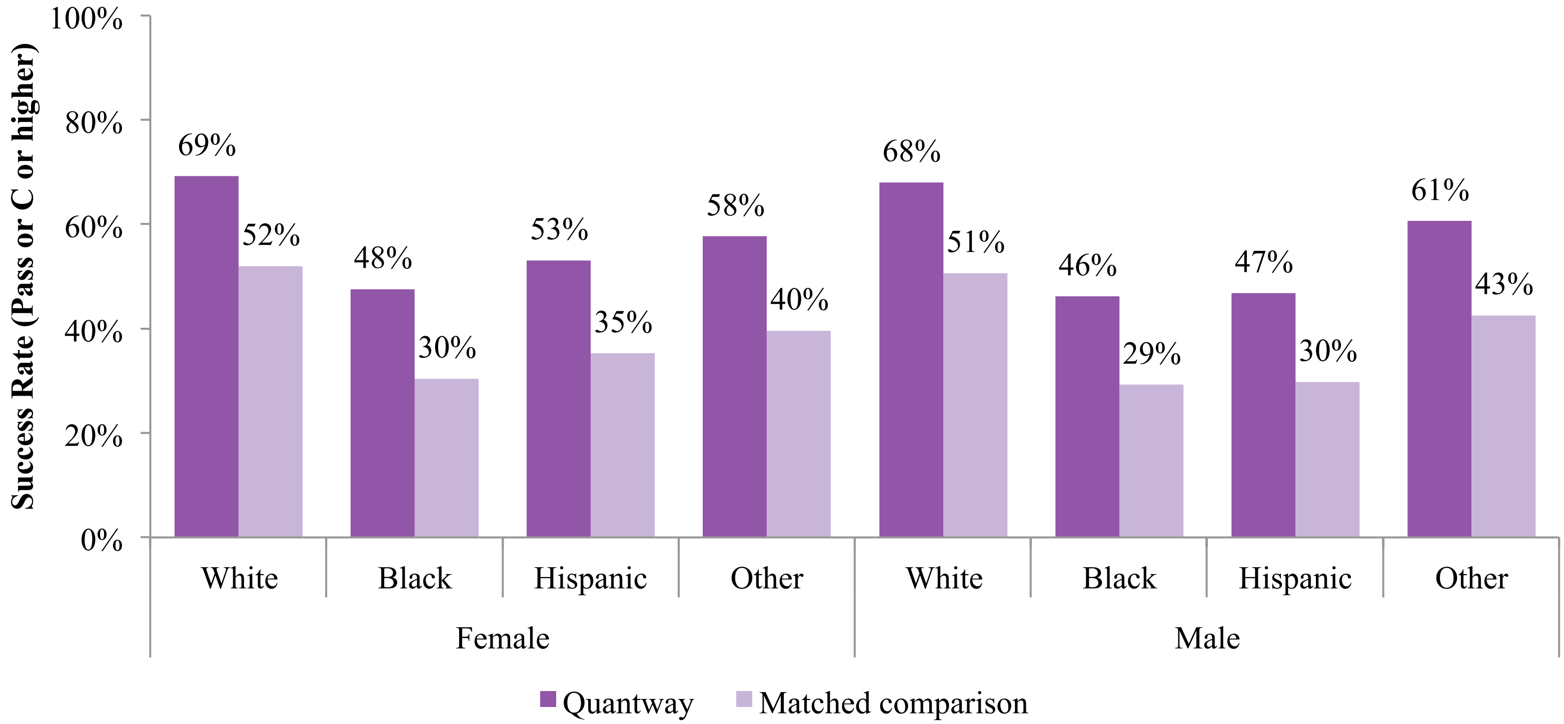


**Figure 5. Model-based success rates by sex and race/ethnicity**

**Carnegie Foundation**
for the Advancement of Teaching

Carnegie Foundation for the Advancement of Teaching
51 Vista Lane
Stanford, California 94305
650-566-5100

Carnegie Foundation for the Advancement of Teaching seeks to vitalize more productive research and development in education. We bring scholars, practitioners, innovators, designers, and developers together to solve practical problems of schooling that diminish our nation's ability to educate all students well. We are committed to developing networks of ideas, expertise, and action aimed at improving teaching and learning and strengthening the institutions in which this occurs. Our core belief is that much more can be accomplished together than even the best of us can accomplish alone.

**www.carnegiefoundation.org**

We invite you to explore our website, where you will find resources relevant to our programs and publications as well as current information about our Board of Directors, funders, and staff.