Carnegie Foundation for the Advancement of Teaching

Do Effects of Quantway® Persist in the Following Year?

A Multilevel Propensity Score Approach to Assessing Student College Mathematics Achievement

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CARNEGIE MATH PATHWAYS TECHNICAL REPORT

Abstract

This report analyzes evidence from a new study assessing the effectiveness of Quantway 1 (QW1), a single-term accelerated developmental math course with a focus on quantitative reasoning. Quantway® is one of the Pathways courses (along with Statway®) developed by a network of faculty and content experts convened by the Carnegie Foundation to accelerate the progress of college students through developmental mathematics with the aim of increasing success rates in earning college credit in mathematics.

This report is the sequel to an earlier study[1] of the effectiveness of QW1, both of which applied a multilevel propensity score matching approach. The first study provided robust evidence that QW1 increases student success in fulfilling developmental math requirements and advances equity in student outcomes. The present study tracked student college math achievement through the year after QW1 enrollment. Results in this most recent analysis revealed that QW1 students were significantly more likely to enroll in credit-bearing college math courses within a year than their counterparts who followed traditional developmental math sequences were, and that while increasing subsequent math course taking, QW1 students demonstrated a comparable GPA. Significantly, QW1 effects were positive across all sex and race/ethnicity subgroups, as well as in nearly all classrooms and colleges. The current study provided additional empirical evidence of the persistence of QW1's effectiveness for diverse student populations across varied classroom and institutional contexts. Directions for future work are discussed.

As indicated in the prior study, additional questions still need to be answered: Do the effects of QW1 persist in the following year? More specifically, we are interested in whether or not QW1 students are (a) more likely than matched comparison students to enroll in credit-bearing college math courses, and (b) perform comparably to or better than matched comparison students in college math courses. Because QW1 is designed not only to get students through their developmental math sequences but to help them meet their college-level math requirements, these questions will be particularly important to answer in determining QW1's effectiveness. Therefore, the objective of the current study is to assess the persistence of effects of QW1 by tracking student college math achievement one year after QW1 participation.

Method

Propensity Score Matching

Propensity score matching is a statistical technique applied to observational data to reduce possible selection bias—where certain kinds of students may have been more likely to enroll in QW1, leading to more positive outcomes than there otherwise would have been—and, accordingly, increase the validity of causal inference (Rosenbaum & Rubin, 1983). There are two main steps involved in this procedure: (a) obtain a propensity score per student, which represents the likelihood of a student enrolling in QW1, and (b) identify as matches students whose propensity scores are similar to each other. Typically, a logistic regression approach is

[1] See Yamada, H., Bohannon, A., & Grunow, A. (2016)

used with a set of factors or covariates hypothesized to influence student enrollment in QW1. To obtain propensity scores in the earlier study (Yamada et al., 2016), we selected 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 based on prior research findings and advice from institutional researchers in the participating colleges and ran a hierarchical linear modeling (HLM) approach (Hong & Raudenbush, 2005, 2006; Raudenbush & Bryk, 2002; Yamada & Bryk, 2016).

In step two, 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). For more details regarding propensity score matching see Yamada et al. (2016).

Analytic Sample

In our earlier matching study, we identified a total of 16,440 students (3,992 QW1 students and 12,448 matched comparison students) across 10 colleges, leading to an average of approximately three matched students for each QW participant (Yamada et al., 2016). In the current study, however, we had to reduce the analytic sample to 10,184 students (2,406 QW1 students and 7,778 matched comparison students) across nine colleges due to the unavailability of course-taking data after QW1 enrollment. The ratio of program students to comparison group students remained the same at 1:3.

Study Design

As student follow-up measures, we looked at (a) student enrollment in college-level math courses in the subsequent calendar year, including a summer term where applicable (e.g., tracking student math course enrollments over the spring, summer, and fall terms for the fall cohorts), and (b) their corresponding GPA[2] in any math courses taken. We tracked these two measures right after QW1 enrollment for QW1 students. For matched comparison students, we tracked the same outcomes over the same time period right after (a) they had successfully completed their developmental math sequences (e.g., completing the requirements in one semester), or (b) the entire academic year regardless of their success in developmental math sequences.

Similar to the previous study (Yamada et al., 2016), we applied a four-level hierarchical linear modeling (HLM) approach (Raudenbush & Bryk, 2002), in which matched clusters (level 1) were nested within QW1 students (level 2), who were in turn nested within QW1 faculty

[2] We assigned a value of 0 as a a grade point to W (Withdrawal) and I (Incomplete) in this analysis in order to create a conservative metric while allowing us to maintain all matched students.

member classrooms (level 3) within their colleges (level 4). We estimated QW1's effectiveness by comparing student enrollment rates of QW1 students with their matched comparisons with a binary outcome. Enrollment was defined as at least one attempt at a college math course. For the analysis of college math GPA, we treated it as a continuous outcome and estimated an effect of QW1 on the GPA. We used HLM 7 (Raudenbush, Bryk, Cheong, Congdon, & du Toit, 2011) for all of the HLM analyses.

Analytic Approach

College Math Enrollment

To estimate differences in college math enrollment rates, we constructed a four-level Bernoulli model and estimated its model parameters using maximum likelihood via penalized quasi-likelihood estimation. ϕ_{ijkl} represents the probability that student *i* matched with QW1 student *j* associated with faculty member *k*'s class in college *l* successfully completed the developmental math sequence. Correspondingly, η_{ijkl} is the corresponding log-odds of this outcome and formally expressed as:

Level 1 Model (Matched cluster)

$\mathrm{Prob}(ATT_{ijkl}=1|\pi_{jkl}) = \phi_{ijkl}$,

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

$\eta_{ijkl} = \pi_{0jkl} + \pi_{1jkl}*(QW_{ijkl}) + \ + \pi_{2jkl}*(PS_{ijkl})$,

Level 2 Model (QW1 Student)

$\pi_{0jkl} = \beta_{00kl} + \beta_{01kl}(W12_{jkl}) + \beta_{02kl}(S12_{jkl}) + \beta_{03kl}(F12_{jkl}) + \beta_{04kl}(S13_{jkl}) + r_{0jkl}$,

$\pi_{1jkl} = \beta_{10kl} + \beta_{11kl}(W12_{jkl}) + \beta_{12kl}(S12_{jkl}) + \beta_{13kl}(F12_{jkl}) + \beta_{14kl}(S13_{jkl}) + r_{1jkl}$,

$\pi_{2jkl} = \beta_{20kl}$,

Level 3 Model (Faculty)

$\beta_{00kl} = \gamma_{000l} + u_{00kl}$,

$\beta_{01kl} = \gamma_{010l}$,

$\beta_{02kl} = \gamma_{020l}$,

$\beta_{03kl} = \gamma_{030l}$,

$\beta_{04kl} = \gamma_{040l}$,

$\beta_{10kl} = \gamma_{100l} + u_{10kl}$,

$\beta_{11kl} = \gamma_{110l}$,

$\beta_{12kl} = \gamma_{120l}$,

$\beta_{13kl} = \gamma_{130l}$,

$\beta_{14kl} = \gamma_{140l}$,

$\beta_{20kl} = \gamma_{200l}$,

Level 4 Model (College)

$\gamma_{000l} = \delta_{0000} + v_{000l}$

$\gamma_{010l} = \delta_{0100}$,

$\gamma_{020l} = \delta_{0200}$,

$\gamma_{030l} = \delta_{0300}$,

$\gamma_{040l} = \delta_{0400}$,
$\gamma_{100l} = \delta_{1000} + v_{100l}$,
$\gamma_{110l} = \delta_{1100}$,
$\gamma_{120l} = \delta_{1200}$,
$\gamma_{130l} = \delta_{1300}$,
$\gamma_{140l} = \delta_{1400}$,
$\gamma_{200l} = \delta_{2000}$,

where *ATT* represents college math enrollment (1 for having attempted at least one course and 0 for not having attempted), and *QW* is a dummy variable indicating whether the student was enrolled in QW1 (coded as 1) or one of the matched comparisons (coded as 0). As a further safeguard, we included individual students' propensity scores, *PS*, as an additional adjustment variable. *W12* to *S13*, which are dummy variables for the four cohort groups with Fall 2013 as a reference category, were included at Level 2 as additional adjustment variables for the outcome.

Results

The analysis indicates that QW1 students are more significantly more likely to take an additional college math course compared to their peers in remedial math classes. The findings, illustrated in Table 1, indicate, on average, QW1 students demonstrated significantly higher odds of enrollment, 2.33 (95% CI [1.49, 3.66][3]), suggesting that the odds of QW1 students taking at least one college math course was 2.33 times as large as the matched comparison students.[4] The corresponding estimated probabilities of enrollment were 50.35% for the QW1 group and 30.31% for the matched comparison group, suggesting that about half of the QW1 students enrolled in at least one college math course in the subsequent year, and that less than a third of the matched comparison students did so. The estimated correlations between the intercept and the slope at both college and faculty levels were negative (-.55 and -.81, respectively), suggesting that the lower the college math enrollment rate for the matched comparison group, the larger the effect of QW1, and that this tendency was stronger among classrooms than among colleges. Effectively, QW1 students at schools where traditional remedial math students are less likely to take college level math were, in fact, even more likely than their peers to take additional math classes. In addition, we found variation (0.299 and 0.094 for the college and faculty variances) in QW1 effect among colleges and faculty members. Figures 1 and 2 display the variation in QW1 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 QW1, 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). A value of 0 in logits means no QW1 effects. Figure 1 demonstrates that there were positive QW1 effects on student

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

[4] We also conducted sensitivity analyses (Hong & Raudenbush, 2005, 2006) on a QW1 effect on college math enrollment. Results indicated that with an adjustment for the largest potential hidden bias, the 95% confidence interval for the new QW1 effect estimates did not contain 0 or any negative values, thereby supporting the strong ignorability assumption. Thus, it is very unlikely that our general conclusion regarding the positive effect of QW1 on the student outcome has been influenced by the omission of unmeasured confounding factors.

outcomes in all colleges. College 8 stands out as a positive deviant with a QW1 effect outside the upper bound of the average effect. Figure 2 shows the variation in QW1 effectiveness across the classrooms in the NIC. The vast majority of QW1 faculty at College 8 drastically outperformed the average QW1 faculty, suggesting internal coherence at this institution. In contrast, a wide range of variation was observed among faculty members at College 3. These patterns in Colleges 8 and 3 were consistent with those found in the previous study in the size of the QW1 effect on fulfilling developmental math course requirements (Yamada et al., 2016).

College Math Performance

To estimate differences in college math GPAs, we constructed a four-level normal model and estimated its model parameters using maximum likelihood via full maximum likelihood estimation.[5] $CMGPA_{ijkl}$ represents college math GPA that student *i* matched with QW1 student *j* associated with faculty member *k*'s class in college *l* earned and is formally expressed as:

Level-1 Model (Matched cluster)

$$CMGPA_{ijkl} = \pi_{0jkl} + \pi_{1jkl}*(PS_{ijkl}) + \pi_{2jkl}*(QWEC_{ijkl}) + \pi_{3jkl}*(CMATTEC_{ijkl}) + \pi_{4jkl}*(CMINT_{ijkl}) + e_{ijkl},$$

Level-2 Model (QW1 student)

$$\pi_{0jkl} = \beta_{00kl} + \beta_{01kl}*(W12_{jkl}) + \beta_{02kl}*(S12_{jkl}) + \beta_{03kl}*(F12_{jkl}) + \beta_{04kl}*(S13_{jkl}) + r_{0jkl},$$
$$\pi_{1jkl} = \beta_{10kl},$$
$$\pi_{2jkl} = \beta_{20kl} + \beta_{21kl}*(W12_{jkl}) + \beta_{22kl}*(S12_{jkl}) + \beta_{23kl}*(F12_{jkl}) + \beta_{24kl}*(S13_{jkl}) ,$$
$$\pi_{3jkl} = \beta_{30kl} + \beta_{31kl}*(W12_{jkl}) + \beta_{32kl}*(S12_{jkl}) + \beta_{33kl}*(F12_{jkl}) + \beta_{34kl}*(S13_{jkl}) ,$$
$$\pi_{4jkl} = \beta_{40kl} + \beta_{41kl}*(W12_{jkl}) + \beta_{42kl}*(S12_{jkl}) + \beta_{43kl}*(F12_{jkl}) + \beta_{44kl}*(S13_{jkl}) ,$$

Level-3 Model (Faculty)

$$\beta_{00kl} = \gamma_{000l} + u_{00kl},$$
$$\beta_{01kl} = \gamma_{010l},$$
$$\beta_{02kl} = \gamma_{020l},$$
$$\beta_{03kl} = \gamma_{030l},$$
$$\beta_{04kl} = \gamma_{040l},$$
$$\beta_{10kl} = \gamma_{100l},$$
$$\beta_{20kl} = \gamma_{200l},$$
$$\beta_{21kl} = \gamma_{210l},$$
$$\beta_{22kl} = \gamma_{220l},$$
$$\beta_{23kl} = \gamma_{230l},$$
$$\beta_{24kl} = \gamma_{240l},$$
$$\beta_{30kl} = \gamma_{300l},$$
$$\beta_{31kl} = \gamma_{310l},$$
$$\beta_{32kl} = \gamma_{320l},$$
$$\beta_{33kl} = \gamma_{330l},$$

[5] We also ran a series of random slope models. However, we observed high correlations involved in the slopes and the intercept, which suggested a fixed slope model. Results from those random slope models were very similar to those from the fixed slope model.

$\beta_{34kl} = \gamma_{340l}$,
$\beta_{40kl} = \gamma_{400l}$,
$\beta_{41kl} = \gamma_{410l}$,
$\beta_{42kl} = \gamma_{420l}$,
$\beta_{43kl} = \gamma_{430l}$,
$\beta_{44kl} = \gamma_{440l}$,

Level-4 Model (College)

$\gamma_{000l} = \delta_{0000} + v_{000l}$,
$\gamma_{010l} = \delta_{0100}$,
$\gamma_{020l} = \delta_{0200}$,
$\gamma_{030l} = \delta_{0300}$,
$\gamma_{040l} = \delta_{0400}$,
$\gamma_{100l} = \delta_{1000}$,
$\gamma_{200l} = \delta_{2000}$,
$\gamma_{210l} = \delta_{2100}$,
$\gamma_{220l} = \delta_{2200}$,
$\gamma_{230l} = \delta_{2300}$,
$\gamma_{240l} = \delta_{2400}$,
$\gamma_{300l} = \delta_{3000}$,
$\gamma_{310l} = \delta_{3100}$,
$\gamma_{320l} = \delta_{3200}$,
$\gamma_{330l} = \delta_{3300}$,
$\gamma_{340l} = \delta_{3400}$,
$\gamma_{400l} = \delta_{4000}$,
$\gamma_{410l} = \delta_{4100}$,
$\gamma_{420l} = \delta_{4200}$,
$\gamma_{430l} = \delta_{4300}$,
$\gamma_{440l} = \delta_{4400}$,

where *QWEC* indicates whether the student was enrolled in QW1 (coded as 1) or one of the matched comparisons (coded as -1), *CMATTEC* represents college math enrollment (1 for having attempted at least one course and -1 for not having attempted), and *CMINT* is an interaction term of these two variables. We applied effect coding to the grouping variables in order to directly represent both main and interaction effects on the outcome. As a further safeguard, we included individual students' propensity scores, *PS*, as an additional adjustment variable. *W12* to *S13*, which are dummy variables for the four cohort groups with Fall 2013 as a reference category, were included at Level 2 as additional adjustment variables for the outcome.

Overall, QW1 students had similar GPAs to other remedial math students who completed college level math courses. Our main focus was on the interaction effect between QW1 and college math enrollment because we were interested to see, among those who enrolled in college math courses, whether the college math GPA earned by QW1 students was lower or higher than, or comparable to, the matched comparison students. The results (presented in Table 2) indicate a significant interaction effect of QW1 and college math enrollment (as well as significant main effects of these two variables). For ease of interpretation, we transformed the model-based results into group mean GPAs and found that the GPAs for the QW1 group and the matched comparison group were comparable at 2.22 and 2.06, respectively. Significant variation among colleges was also observed (0.010); however, the variation pertained to the intercept (grand mean of GPA), but not the slope (effect size of QW1 on GPA).[6] Overall, the results derived from college math enrollments and GPA suggested that QW1 students were more likely than comparable students who enrolled in traditional developmental math sequences to enroll in a college math course in the following year and to demonstrate comparable performance in college math.

Subgroup Analyses

To examine possible differential effects of QW1 by sex and race/ethnicity subgroups, we constructed four-level HLMs similar to those described above. In this subgroup analysis we applied effect coding to the grouping variables in order to directly represent both main and interaction effects in the outcome. The reference categories were female and White (since that demographic group was the largest in the sample), and each of these was coded as -1.[7] We excluded cases where sex hadn't been specified. Figures 3 and 4 present the model-based results transformed back into their natural metrics of proportion of students enrolling in college math courses and earning an associated GPA, respectively. Positive effects of QW1 were observed for all subgroups. More specifically, Black and Hispanic male students, as well as Black female students, exhibited the largest increase in college math enrollment rates relative to the corresponding subgroups of matched comparison students, suggesting that they benefited most from QW1. Each subgroup of students also showed a college math GPA comparable to its matched comparison students.

Discussion

This study is a sequel to the previous causal-analytic study (Yamada et al., 2016), assessing QW1's effectiveness on student college math achievement by tracking the propensity score matched students throughout the year after QW1 enrollment. We measured two follow-up outcomes: college math enrollment as engagement and an associated college math GPA as performance. The results revealed that half of QW1 students enrolled in college math courses within a year, whereas only one-third of their counterparts who followed traditional developmental math sequences did so, and that QW1 students demonstrated a comparable GPA. It is plausible that the former may be a consequence of QW1's emphasis on strengthening growth mindset of students as mathematical learners and doers, enhancing their sense of belonging in a mathematical environment, and helping them develop the confidence and tenacity to grapple with the complex language of mathematics. Accordingly, QW1 students persisted and engaged more in college-level mathematics in the subsequent year.

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[6] The obtained result does not necessarily mean no variation in QW1 effect size among colleges. Data analyzed in this study were from the relatively small number of colleges (9 colleges), and it might be possible that we would detect significant, meaningful variation with more colleges.

[7] Because we included interaction terms of those two sets of effect-coded demographic groups, the actual reference group in the HLM models was white female.

Another focus of our analysis was on variation in QW1 effect among different colleges, faculty, and student subgroups. To advance efficacy reliably at scale, QW1 should work for diverse student populations across a wide range of classroom and institutional contexts. Therefore, it is critical to learn from variation and find a way to reduce variation in desired outcomes (Bryk, Gomez, Grunow, & LeMahieu, 2015). Our results indicated that QW1 effects were positive across all sex and race/ethnicity subgroups of students, as well as nearly all classrooms and colleges, suggesting that QW1 reduced variability in student outcomes and promoted positive outcomes across subgroups. Interestingly, one college identified as a positive deviant in the previous study demonstrated the similar pattern of success in college math achievement: it outperformed other colleges and maintained high performance across all the classrooms in the college (see College 8 in Figures 1 and 2). This college may make a great case from which to learn how effectively and reliably it adapted QW1 into its local context. We can then spread its practices to other institutions nationwide and facilitate network-wide improvement through improvement science embedded in the networked improvement community (Bryk et al., 2015).

Finally, it is worth mentioning a future direction for further exploration. We are currently analyzing data obtained from the National Student Clearinghouse. Our particular interest is in 2-year and 4-year degree completion rates as well as transfer rates into 4-year colleges of QW1 students as more distal outcomes. This analysis would further illuminate the extent and dimensions of QW1's effectiveness.

References

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

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.

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.

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

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.

Yamada, H., Bohannon, A., & Grunow, A. (2016). *Assessing the effectiveness of Quantway®: A multilevel model with propensity score matching.* Stanford, CA: Carnegie Foundation for the Advancement of Teaching.

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.
Model-Based Estimation of QW1 Effect on College Math Enrollment Rate

Fixed effect	Coefficient	*SE*	*t*	*p*	Odds ratio
Intercept	-1.11	0.17	-6.68	<0.001	0.33
W12	0.63	0.17	3.62	<0.001	1.87
S12	-0.08	0.09	-0.89	.372	0.92
F12	0.00	0.08	-0.01	.990	1.00
S13	-0.52	0.08	-6.44	<0.001	0.59
QW1	0.85	0.21	3.99	.001	2.33
W12	-0.24	0.34	-0.71	.476	0.79
S12	0.24	0.18	1.32	.188	1.27
F12	0.31	0.16	1.96	.050	1.37
S13	-0.02	0.14	-0.15	.878	0.98
Propensity score	0.19	0.03	6.70	<0.001	1.21
Random effect at level 4 (college)	Variance	*df*	χ^2	*p*	Correlation
Intercept	0.219	8	154.40	<0.001	-0.55
QW1	0.299	8	66.07	<0.001	
Random effect at level 3 (faculty)	Variance	*df*	χ^2	*p*	Correlation
Intercept	0.013	44	60.36	0.051	-0.81
QW1	0.094	44	76.14	0.002	

Table 2.
Model-Based Estimation of QW1 Effect on College Math GPA

Fixed effect	Coefficient	*SE*	*t*	*p*
Intercept	0.57	0.04	14.50	<0.001
W12	-0.10	0.08	-1.18	.239
S12	-0.13	0.04	-2.80	.006
F12	-0.11	0.04	-2.79	.006
S13	-0.27	0.03	-7.89	<0.001
QW1	0.04	0.01	3.78	<0.001
W12	0.10	0.06	1.76	.078
S12	0.08	0.03	2.59	.010
F12	0.07	0.03	2.52	.012
S13	0.05	0.03	1.91	.056
College math enrollment	1.03	0.01	87.80	<0.001
W12	-0.19	0.06	-2.99	.003
S12	-0.13	0.03	-3.74	<0.001
F12	-0.07	0.03	-2.33	.020
S13	-0.03	0.03	-0.91	.363
QW1 x College math enrollment	0.04	0.01	3.87	<0.001
W12	0.10	0.06	1.63	.102
S12	0.06	0.03	1.84	.065
F12	0.05	0.03	1.75	.080
S13	0.06	0.03	2.00	.046
Propensity score	0.07	0.01	4.75	<0.001
Random effect at level 4 (college)	Variance	*Df*	χ^2	*p*
Intercept	0.010	8	77.95	<0.001
Random effect at level 3 (faculty)	Variance	*Df*	χ^2	*p*
Intercept	0.002	44	60.36	0.051

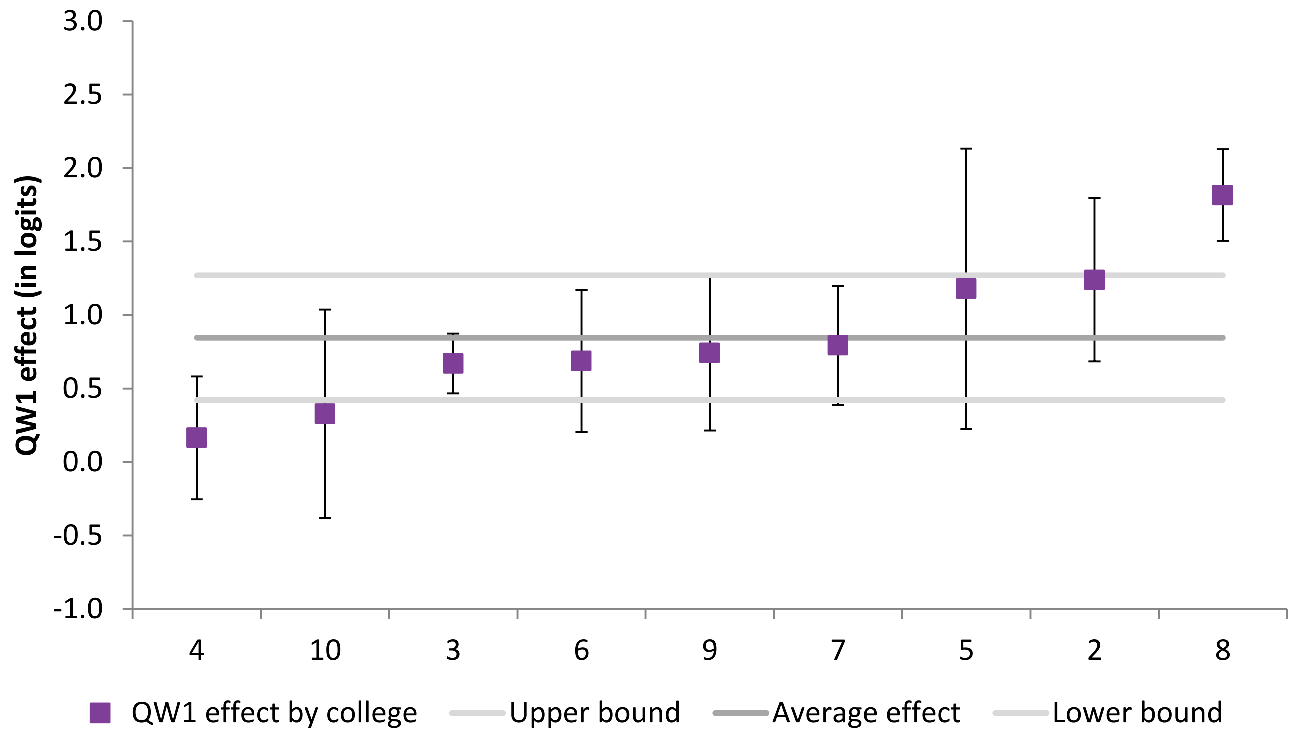

Figure 1. Variation in QW1 effect on college math enrollment rates among colleges.

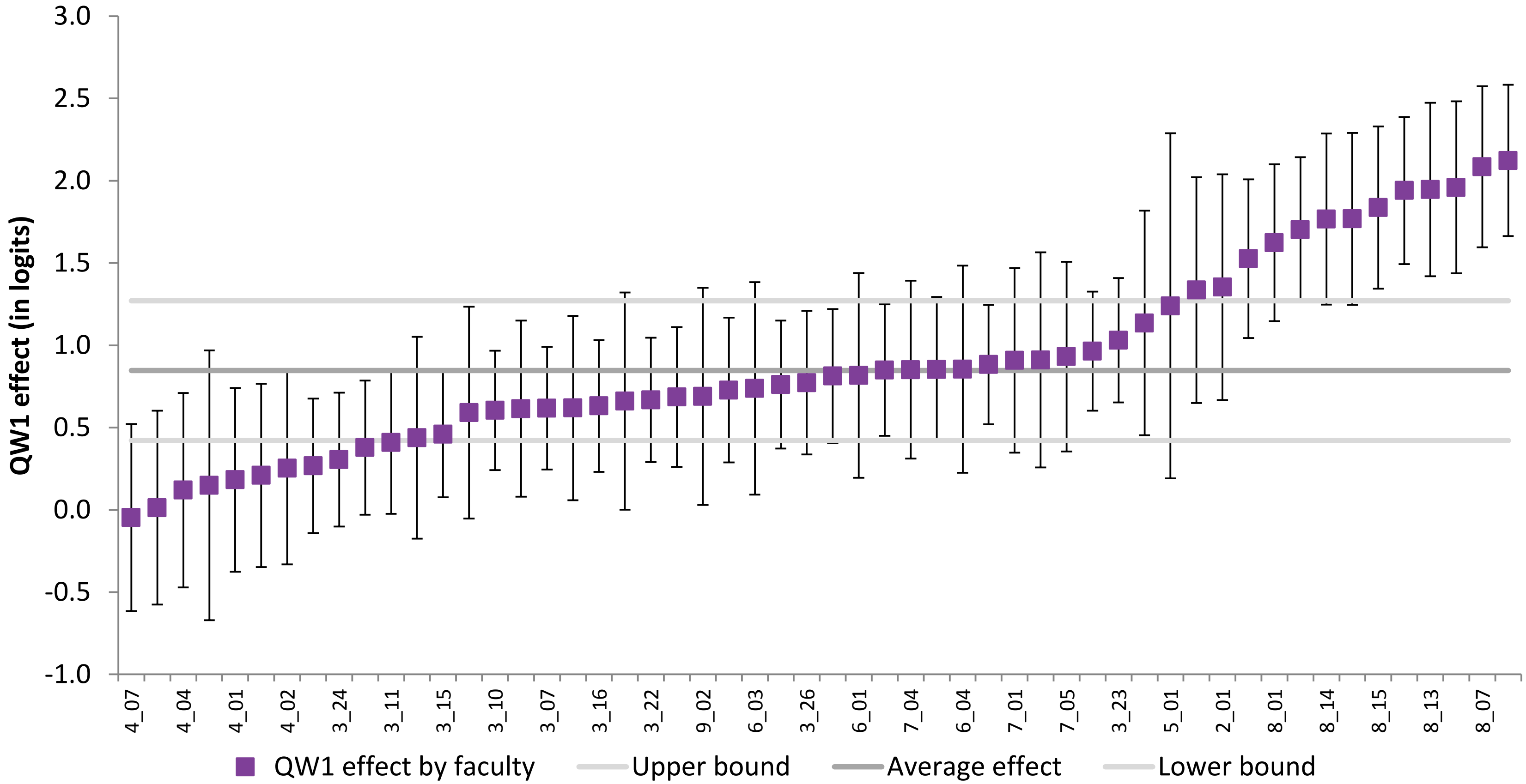

Figure 2. Variation in QW1 effect on college math enrollment rates among faculty members.

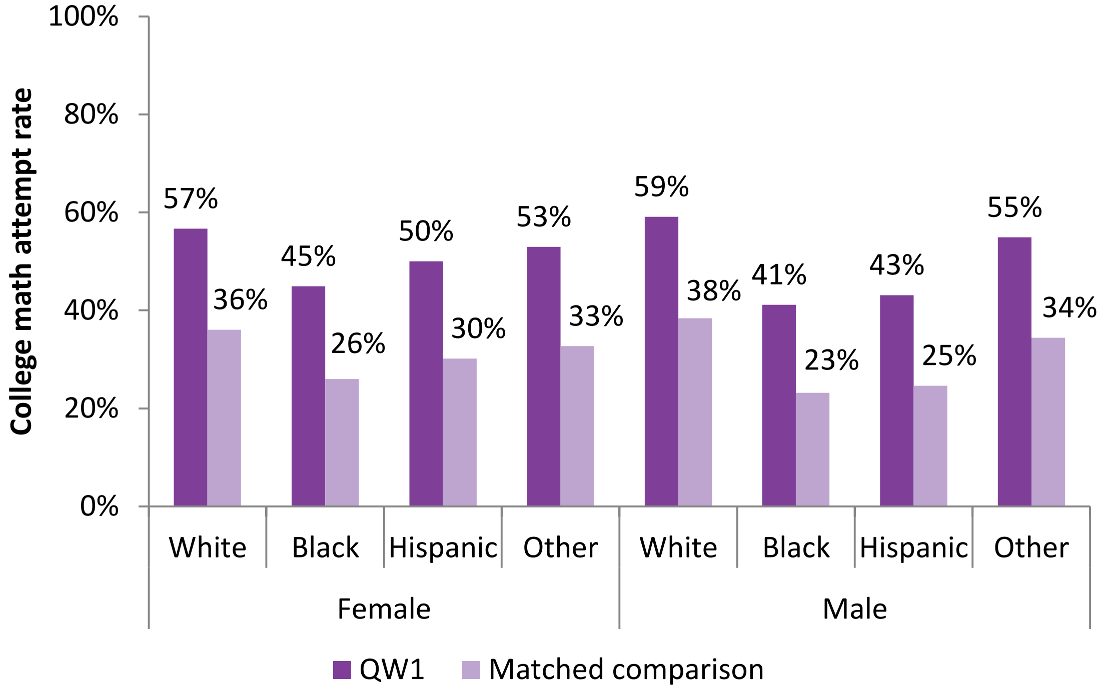

Figure 3. Model-based college math enrollment rates by sex and race/ethnicity.

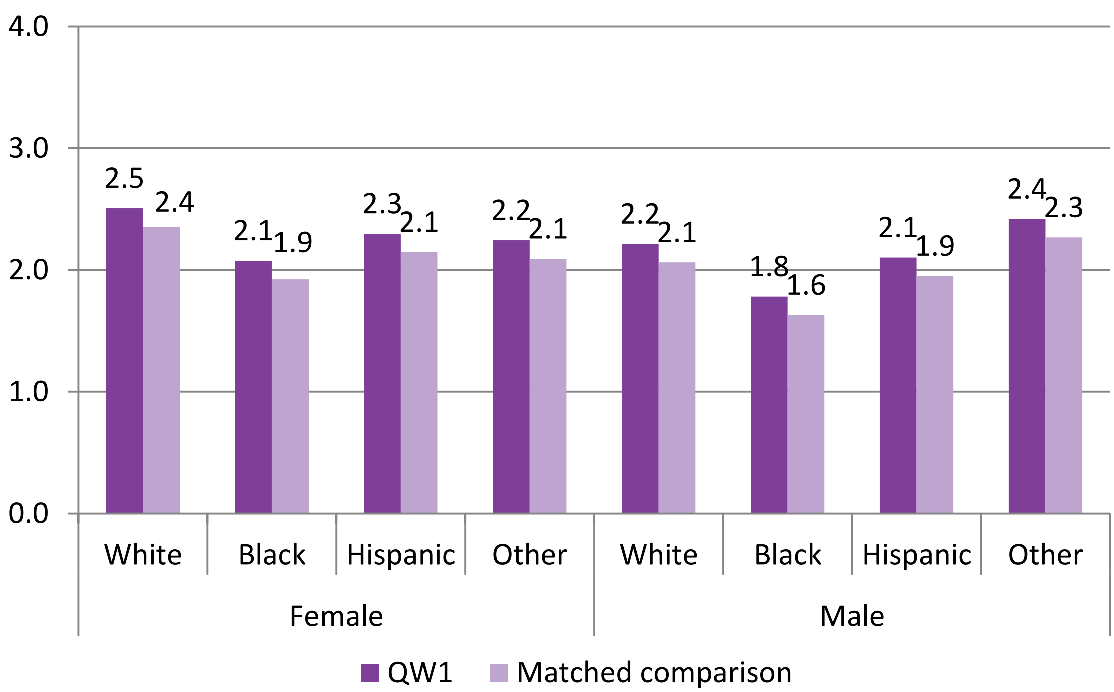

Figure 4. Model-based college math GPA by sex and race/ethnicity.

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