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The Research Alliance for New York City Schools

Postsecondary Analysis Brief: Technical Appendix

Deeper Learning and College Enrollment

What Happens After High School?

2016

The postsecondary brief updates the findings in the third report of the *Study of Deeper Learning: Opportunities and Outcomes*. The study design, sampling, and methods described in this appendix are similar to those that were used to determine the impact of attending a deeper learning network high school on postsecondary enrollment in the original study (Zeiser, Rickles, Taylor, & Garet, 2014).

A. Sample

Each of the 20 network high schools selected for the original study was affiliated with one of ten networks that participated in the William and Flora Hewlett Foundation's Deeper Learning Community of Practice.[1] These ten networks all have a well-established history of promoting deeper learning, and share an emphasis on providing educational opportunities for minority students and students from low-income families to prepare them for college and career. For the original study, we selected regular, non-magnet network high schools (serving students in Grades 9 to 12) that became associated with the network before or during the 2007–08 academic year. We also limited our sample to schools that, based on information from network representatives, had a moderately or well implemented approach to promoting deeper learning that was used with all students in the school. Finally, we limited our sample to schools that had at least 200 students and schools where at least 25 percent of the students were eligible for free or reduced-price lunch. While we originally recruited 20 network high schools for the study, we obtained student-level background and postsecondary data for 14 network high schools. Given the small number of network schools in the sample, and given the criteria used to select the sample, the study's findings do not generalize to all network schools associated with the participating deeper learning networks.

For each network high school selected for the original study, we identified a matched non-network high school in the same district or geographical area.[2] Similar to the network high schools, selected non-network high schools had to be regular, non-magnet, non-charter[3] high schools serving at least 200 students in Grades 9 to 12. In addition, the non-network high schools had to be in existence during the 2007–08 academic year, and had to be schools where at least 25 percent of students were eligible for free or reduced-price lunch between the 2007–08 and 2009–10 school years.

To select matched non-network high schools, we identified schools with a population of incoming Grade 9 students similar to the incoming Grade 9 students at each of the network schools using the following characteristics that were available in

[1] Participating networks included Asia Society, Big Picture Learning, ConnectEd/Linked Learning, EdVisions Schools, Envision Schools, Expeditionary Learning (now EL Education), High Tech High, Internationals Network for Public Schools, New Tech Network, and New Visions for Public Schools.

[2] Four of the network schools in the original study were not matched to a non-network high school due to (1) difficulties obtaining student-level data or (2) the absence of an appropriate comparison school within the geographical area.

[3] Four of the network high schools included in the analyses of postsecondary data are charter schools. The matched non-network schools are not charter schools.

the National Center for Education Statistics' 2008–09 and 2009–10 *Common Core of Data* (*CCD*): the average percentage of students eligible for free or reduced-price lunch, the percentage of African-American students, the percentage of Hispanic students, and the percentage of white students. To guard against matching dissimilar schools, we required comparison schools to be within one standard deviation of their paired network school on each of these four variables. After receiving extant district data, we also compared the Grade 8 achievement of students in the network school and students in the selected comparison schools to determine the best match for each network high school.

The sample used for the updated analyses presented in the brief differs from the sample used for the analyses performed in the original study in two ways:

- The postsecondary analyses in the original report were based on the three cohorts of students who entered Grade 9 between 2007–08 and 2009–10. The updated analyses included an additional cohort, those who entered Grade 9 in 2010–11.
- The updated analyses included postsecondary data for Pair 4 and Pair 5, which were excluded from the original study because we were not able to obtain their postsecondary data in time to include them in the original study.

Exhibit A.1 lists the pairs of schools included in the updated analyses of postsecondary data and presents the demographic characteristics of these schools.

Exhibit A.1. Characteristics of Schools Included in the Updated Postsecondary Enrollment Analyses

		Enrollment	% Female	% African American	% Hispanic	% Asian	% FRPL
Pair 1 (CA)	Network (1N)	400	70	30	40	10	70
	Non-Network (1C)	2100	50	20	20	30	40
Pair 2 (CA)	Network (2N)	300	50	10	40	0	40
	Non-Network (2C)	1600	50	20	30	10	50
Pair 4 (CA)	Network (4N)	300	50	0	90	10	50
	Non-Network (4C)	2300	50	0	90	10	70
Pair 5 (CA)	Network (5N)	400	50	0	100	0	40
	Non-Network (4C)	2300	50	0	90	10	70
Pair 6 (CA)	Network (6N)	600	50	10	10	10	30
	Non-Network (6C)	2600	50	10	30	0	20
Pair 7 (CA)	Network (7N1)	400	50	10	10	10	40
	Network (7N2)	400	50	10	10	10	40
	Non-Network (7C)	2500	50	10	30	10	50
Pair 8 (NY)	Network (8N)	500	60	10	20	10	40
	Non-Network (8C)	600	60	10	20	20	50
Pair 9 (NY)	Network (9N)	400	60	40	60	0	80
	Non-Network (9C)	400	40	40	50	0	70
Pair 10 (NY)	Network (10N)	400	40	0	40	60	100
	Non-Network (10C1)	600	50	0	100	0	80
	Non-Network (10C2)	500	50	0	90	10	90

		Enrollment	% Female	% African American	% Hispanic	% Asian	% FRPL
Pair 11 (NY)	Network (11N)	400	50	20	40	30	100
	Non-Network (10C1)	600	50	0	100	0	80
	Non-Network (10C2)	500	50	0	90	10	90
Pair 13 (NY)	Network (13N)	400	60	80	20	0	80
	Non-Network (13C)	400	60	70	20	0	80
Pair 14 (NY)	Network (14N)	400	50	80	20	0	100
	Non-Network (14C)	500	50	80	10	0	70
Pair 15 (NY)	Network (15N)	300	50	40	60	0	70
	Non-Network (9C)	400	40	40	50	0	70

Notes: Pair 3 and Pair 12, which were included in analyses of student survey and high school graduation data in the original study, are omitted from analyses of postsecondary enrollment because we were unable to obtain postsecondary data from the matched non-network schools. FRPL = free or reduced-price lunch. School demographic data came from the 2010–11 *Common Core of Data* (*CCD*). To ensure school confidentiality, enrollment is rounded to the nearest 100 students and percentages are rounded to the nearest 10 percent.

Details on Specific School Pairs

Schools 4N and 5N are located in the same district, and we were able to recruit only a single non-network school in this district. The students in this non-network school were matched to students in both School 4N and School 5N. Schools 7N1 and 7N2 were associated with the same deeper learning network and resided on the same campus. Because the schools were small in size, we combined the students attending them and treated them as single network school, comparing it with 7C. Due to small sample sizes, Schools 10C1 and 10C2 were combined and treated as a single non-network school. Both non-network schools served populations that were similar to Schools 10N and 11N (network schools), which were associated with the same deeper learning network. The propensity scores for Pairs 10 and 11 were based on a combined sample that included both Schools 10N and 11N (network schools) and Schools 10C1 and 10C2 (non-network schools), because of the limited sample size within the individual network and non-network schools. Pairs 10 and 11 were considered separate pairs for the purposes of the impact analysis and meta-analysis. School 15N (a network school) was matched with School 9C (a non-network school), which was also used as the non-network school for School 9N (a network school).

B. Methods

Weighting for Student Selection Into Network Schools

Students were not randomly assigned to network and non-network schools, so network and non-network school students may not have had equivalent characteristics when entering high school. These pre-existing student differences mean that any claims about a network school's effects on student experiences and outcomes could be biased if they are based on direct comparisons between network and non-network school students. To account for these preexisting differences, we used inverse probability of treatment weighting (IPTW), which adjusts the comparison student sample to be more similar to the network school student sample based on measured student background characteristics. Assuming the measured student background characteristics accurately capture the important pre-existing differences between network and non-network school students, IPTW allows us to obtain valid estimates about what network school students would have experienced if they had attended the non-network school.

IPTW is a propensity score-based method for selection bias adjustment (Hirano, Imbens, & Ridder, 2003). A student's propensity score (P_i) is his or her predicted probability of attending a network school instead of a non-network school, given the measured student characteristics (X_i). To estimate propensity scores, we estimated separate logistic regression models for each school pair (j) and student cohort (k):

Equation 1. $\ln\left(\frac{p_{ijk}}{1-p_{ijk}}\right) = \beta_{0jk} + \beta_{1jk}X_{ijk},$

where X_{ijk} represents the following student characteristics (when available for a given school pair): gender, race/ethnicity, parents' education, eligibility for free or reduced-price lunch, English language learner status, whether the student has an individualized education plan, Grade 8 achievement test scores in mathematics and English language arts (ELA), Grade 8 attendance rates, and age at Grade 9 entry.

For each student who attended a network school, the IPTW weight had a value of 1. For each non-network school student, the IPTW weight was calculated based on the student's predicted probability of treatment assignment (i.e., the estimated propensity score). Thus, for both groups, the weight can be expressed as:

Equation 2. $w_{ijk} = T_{ijk} + \left(1 - T_{ijk}\right)\frac{p_{ijk}}{1-p_{ijk}},$

where T_{ijk} equals 1 for students attending a network school and 0 for students attending a non-network school student. With this weight, the non-network group was weighted to represent the network group to facilitate estimation of the average treatment effect on the treated (ATT).

Within-Pair Effect Estimation: Doubly Robust Regression Model

To estimate the effects of enrolling in a deeper learning network school instead of a non-network school, we first conducted pair-by-pair analyses.[4] The analysis method is considered doubly robust (Funk, Westreich, Wiesen, Sturmer, Brookhart, & Davidian, 2011) because it accounts for observed differences between network and non-network school students in two ways: (1) through propensity score weighting, and (2) through regression-based covariate adjustment. To apply both the propensity score weight and the regression-based covariate adjustment, we used the following weighted logistic regression model:

Equation 3. $ln\left(\frac{p_{ij}}{1-p_{ij}}\right) = \beta_{0j} + \beta_{1j}T_{ij} + \beta_{2j}X_{ij},$

where P_{ij} is the probability of enrolling in a postsecondary institution[5] for student *i* in school *j*; T_{ij} is a dichotomous indicator for whether the student enrolled in the network school ($T_{ij} = 1$) or the non-network school ($T_{ij} = 0$) in the fall of Grade 9; and X_{ij} is a vector of available student background characteristics, as well as dichotomous indicators for the year in which students entered Grade 9 (between 2007–08 and 2010–11). We applied the IPTW weight, so the estimated effect represents the effect for students who attended a network school in the fall of Grade 9. The main parameter of interest is β_{1j}, which is the effect of attending a network school instead of the matched non-network school in a given school pair.

Subgroup Analysis

We also examined whether the effect of attending a network school on postsecondary enrollment differed across the following subgroups:

- Gender: male versus female
- Free or reduced-price lunch status (FRPL): eligible versus not eligible[6]
- Prior ELA achievement: higher achieving versus lower achieving

[4] We conducted separate pair-specific analyses (instead of combining data into one analysis) for two main reasons. First, data access limitations precluded combining student data from California and New York City. Second, because the available student background characteristics differed across districts, pooling the data would have required restricting the data to a subset of the characteristics. By conducting separate analyses for each pair, we were able to maximize the number of student background characteristics we could include in the analyses.

[5] Other fitted models used the probability of enrolling in a four-year postsecondary institution, probability of enrolling in a two-year postsecondary institution, and probability of enrolling in a selective four-year postsecondary institution as outcomes.

[6] Information regarding students' eligibility to receive free or reduced-price lunch (FRPL), an indicator of low-income status, was not available in all districts.

We compared students' Grade 8 ELA test scores to the state average[7] test score for the year in which the test was taken. Students were classified as lower achieving if their test score fell below the state mean and higher achieving if their score was above the state mean.

To test whether treatment effects differed significantly across subgroups, we estimated a model similar to the model described above, adding the interaction between network school attendance and a dichotomous subgroup indicator:

Equation 4. $ln\left(\frac{p_{ij}}{1-p_{ij}}\right) = \beta_{0j} + \beta_{1j}T_{ij} + \beta_{2j}X_{ij} + \beta_{3j}S_{ij} + \beta_{4j}(S_{ij}\times T_{ij}),$

where S_{ij} is the dichotomous subgroup indicator. In this model, the primary parameter of interest is β_{4j}, which captures the difference in the effects of network school attendance between different subgroups (i.e., differential effect). Each subgroup analysis was performed independently, so only one interaction term was added to the model at a time.

Averaging Pair-Specific Effect Estimates: Meta-Analysis

The results presented in the brief are estimates that have been averaged across school pairs. We view the results as pertaining only to the particular schools included in our sample and not to a wider population. Thus, we used a fixed-effects meta-analysis approach (Hedges & Vevea, 1998) to calculate the average effect across the school pairs.[8] The precision-weighted, fixed-effects meta-analysis was used to combine results across pairs for both the main analyses (which assess the overall effect of attending a network school on college enrollment) and subgroup analyses (which examine whether the effect of attending a network school differed across student subgroups). For the main analyses, the coefficient for the network school indicator was meta-analyzed; for the subgroup analyses, the coefficient for the interaction between the network school indicator and the subgroup membership indicator was meta-analyzed. In both cases, the meta-analysis was based on the following equation:

Equation 5. $\overline{ES} = \frac{\sum_{j=1}^{13} w_j \hat{\beta}_j}{\sum_{j=1}^{13} w_j},$

where $\hat{\beta}_j$ is the estimated effect for pair *j*, and w_j is the inverse of the variance of pair *j*'s estimate (i.e., one divided by the standard error squared). This equation calculates the precision-weighted average of the pair-specific effect estimates, where estimates with more precision (less error variance) receive more weight in the average.

Enrollment Pattern Analyses

For students who ever enrolled in college, we also examined whether they started enrollment immediately after expected high school graduation and whether they were consistently enrolled for at least two, three, and four academic terms. For students who enrolled in college in the first fall after expected high school graduation, we looked at whether they returned to college in the following fall (retention). Enrollment patterns were only observed for students in the first two cohorts (those who entered Grade 9 in 2007–08 or 2008–09) because students in later cohorts had not been out of high school long enough to be observed on all indicators. For each measure, we first calculated school-level weighted means using the IPTW weight. Next, we calculated the weighted

[7] In New York City, test scores were compared to the New York City average ELA test score for the appropriate year.

[8] Meta-analyses may be conducted using either a fixed- or random-effects approach (Hedges & Vevea, 1998). A random-effects meta-analysis would assume that the schools in the study were drawn from a larger population, and the goal of the analysis would be to estimate the average effect of attending a network school for the population.

average of these means separately for network schools and non-network schools (using the sum of students' IPTW weights within schools as the weight for both network and non-network schools). After obtaining the overall means for network schools and non-network schools, a two-sample z test for proportions was conducted to determine if the difference between students who attended network schools and students who attended non-network schools was statistically significant.

Analyses of enrollment trends do not estimate the causal effect of attending a deeper learning network high school because these analyses are based on subsamples of students who enrolled in college. Differences between network and non-network school students within the subsample of students who enrolled in college do not necessarily indicate that attending a network school caused those differences.

C. Results

Exhibit C.1 presents estimates of the effects of attending a deeper learning network school on postsecondary enrollment measures for each pair of schools as well as the average effect across pairs based on a meta-analysis. The estimated effects are reported as odds ratios.

Exhibit C.1. Treatment Effects on Postsecondary Enrollment, by School Pair

School Pair	Effect on Ever Enrolled in Any Institution	Effect on Enrolled in Two-Year Institution	Effect on Enrolled in Four-Year Institution	Effect on Enrolled in Selective Four-Year Institution
Meta-analytic Average	1.13*	1.01	1.30*	1.23*
Pair 1	0.90	1.17	0.67*	0.68
Pair 2	1.19	0.97	1.59	3.89*
Pair 4	1.56*	1.66*	1.33	0.96
Pair 5	1.16	1.34*	0.73	0.59
Pair 6	1.19	0.89	1.60*	1.61*
Pair 7	1.19	0.78	1.81*	1.28
Pair 8	0.97	0.10*	3.37*	0.78
Pair 9	1.03	0.90	1.22	2.68*
Pair 10	0.88	0.81	0.91	0.26
Pair 11	1.81*	1.40*	1.90*	3.04*
Pair 13	1.15	1.33	1.13	0.73
Pair 14	1.00	0.87	1.27	2.57*
Pair 15	0.71	0.72	0.91	1.81

Note: * indicates that the odds ratio is significant at the .05 level.

Exhibit C.2 presents the results of the subgroup analyses for the probability of ever enrolling in a postsecondary institution and the probability of enrolling in a four-year postsecondary institution. Specifically, Exhibit C.2 contains coefficients (odds ratios) for the interaction term in Equation 4, which represents the extent to which the effect of attending a network school on postsecondary enrollment differed between students with different levels of prior achievement. We did not find significant differential effects based on students' gender or eligibility for free or reduced-price lunch (results not shown). We also did not observe subgroup differences in the probability of enrolling in a two-year institution or the probability of enrolling in a selective four-year institution.

In the brief, Exhibit 2 shows (1) the actual enrollment rates for students who entered network high schools with lower and higher levels of prior achievement and (2) the estimated enrollment rates for the two student subgroups among students who attended non-network schools. Relying on NSC data, the actual enrollment rates for network school students were computed by dividing the number of network school students ever enrolled in a postsecondary institution by the total number of network school students (separately for each student subgroup). Estimated enrollment rates for non-network school students were derived from the logit regression coefficients.

Specifically, the subgroup analysis based on Equation 4 estimated the effect of attending a deeper learning network school for students who had higher prior achievement (subgroup = 0) in each pair. Results from the subgroup analysis also allowed us to compute the effect for students who had lower prior achievement (subgroup = 1) in each pair, which is the sum of the coefficient for the indicator for attending a network school and the coefficient for the interaction term.[9] Using meta-analyses, we computed the average effect across pairs for each of the two student subgroups. For each student subgroup, the estimated enrollment rate for non-network school students was then calculated by (1) converting the enrollment rate for network school students in the subgroup into logits, (2) subtracting the average treatment effect (in logits) for the subgroup from the enrollment rate (in logits) for the network school students, and (3) converting the difference (in logits) back to a predicted probability of postsecondary enrollment.

Exhibit C.2. Differential Effect on Postsecondary Enrollment Rates by Students' Prior Achievement Level, by School Pair

School Pair	Differential Effect (Odds Ratio) on Ever Enrolled in Any Institution	Differential Effect (Odds Ratio) on Enrolled in Four-Year Institution
Meta-analytic Average	1.39*	1.76*
Pair 1	1.12	1.53
Pair 2	1.15	1.11
Pair 4	1.45	1.44
Pair 5	2.21*	2.55*
Pair 6	2.37*	2.40*
Pair 7	1.25	1.58
Pair 8	0.92	2.43*
Pair 9	1.10	2.01
Pair 10	N/A	N/A
Pair 11	N/A	N/A
Pair 13	1.05	1.88
Pair 14	1.39	1.55
Pair 15	1.37	1.35

Note: * indicates that the odds ratio is significant at the .05 significance level. N/A denotes that data for prior achievement was not available for students in the school pair.

[9] We also calculated the standard error of this sum of coefficients for each pair based on the standard error of each coefficient and their covariance.

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