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Graduation Advantage Persists for Students in Deeper Learning Network High Schools: Technical Appendix

Updated Findings from the *Study of Deeper Learning: Opportunities and Outcomes*

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This technical appendix provides supporting information for the brief entitled *Graduation Advantage Persists for Students in Deeper Learning Network High Schools*, which updates the findings in the third report of the *Study of Deeper Learning: Opportunities and Outcomes*. The study design, sampling, and methods used for the brief are similar to those used to determine the impact of attending a deeper learning network high school on high school graduation in the original study (Zeiser, Rickles, Taylor, & Garet, 2014).

A. Sample

Each network high school selected for this study was a member of one of ten networks that participated in the William and Flora Hewlett Foundation's Deeper Learning Community of Practice.[1] The ten networks represented in this study have a well-established history of promoting deeper learning, and all share an emphasis on providing educational opportunities for minority students and students from low-income families to prepare them for college and career. We selected one or two high schools from each network, focusing on regular, non-magnet network high schools (serving students in Grades 9 to 12) that were associated with the network 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 deeper learning that was experienced by all students in the school. Finally, we limited our sample to schools that had at least 200 students and where at least 25 percent of the students were eligible for free or reduced-price lunch. Of the 20 network high schools we recruited for the study, we were able to obtained student-level background and graduation data for 14. 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 high schools associated with the participating deeper learning networks.

For each network high school selected for the study, we identified a matched non-network high school in the same district or geographical area. Similar to the network high schools, selected non-network high schools had to be regular, non-magnet, non-charter[2] high schools serving at least 200 students in Grades 9 to 12. Also, we sought non-network high schools that were in existence during the 2007–08 academic year and in which at least 25 percent of students were eligible for free or reduced-price lunch. 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 the National Center for Education Statistics' 2008–09 and 2009–10 Common Core of Data (CCD): the 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 each non-network school to be within one standard deviation of its paired network school on each of these four variables. While we used CCD data to limit the pool of potential non-network schools, after receiving extant district data, we also compared the Grade 8 achievement of students in the network school

[1] Participating networks included Asia Society, Big Picture Learning, ConnectEd, EdVisions Schools, Envision Schools, Expeditionary Learning, High Tech High, Internationals Network for Public Schools, New Tech Network, and New Visions for Public Schools.

[2] Six of the network high schools included in the analyses of graduation data are charter schools. The matched non-network schools are not charter schools.

and students in the selected non-network schools to determine the best match for each network high school.

The sample used for the updated analyses differs from the sample used for the analyses performed in the original study in three ways:

- The graduation 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.
- One school pair (Pair 5), which was included in the original study, was excluded from the update analyses because the network school (5N) ceased to provide graduation data to the district, and we were not able to obtain the data directly from the school.
- The updated analyses included graduation data for Pair 1 and Pair 2, which were excluded from the original study because we were not able to obtain their graduation data in time to include them in the original study.

Exhibit 1 presents the pairs of schools included in the updated analyses of graduation data as well as the demographic characteristics of these schools.

Exhibit 1. Characteristics of Schools Included in the Updated Graduation Analyses

Pair	School	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 3 (CA)	Network (3N)	400	50	20	50	10	60
	Non-Network (3C)	1800	50	40	20	20	50
Pair 4 (CA)	Network (4N)	300	50	0	90	10	50
	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

Pair	School	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 12 (CA)	Network (12N)	300	50	60	30	0	40
	Non-Network (3C)	1800	50	40	20	20	50
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: FRPL = free or reduced-price lunch. School demographic data came from the 2010–11 Common Core of Data (CCD). Due to missing data in the 2010–11 CCD, demographic information for School 3N came from the 2011–12 CCD, and free or reduced-price lunch information for this school came from 2011–12 enrollment data from the California Department of Education. 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:

Pair 5 was not included in the updated analyses because the network school (5N) no longer provides graduation data to the district and we were not able to obtain graduation data from the school.

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 a 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 12N (a network school) was matched with School 3C (a non-network school), which was also used as the non-network school for School 3N (a network school).

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 preexisting 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 non-network school 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 preexisting 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[3] 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 her or his 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. With this weight, the sample of non-network school students was weighted to represent the sample of network school students to facilitate estimation of the average treatment effect on the treated (ATT).

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[3] In our study, network and non-network school attendance is defined based on where students enrolled in the fall of Grade 9. This measure does not change if students transferred to another school after Grade 9 entry.

Within-Pair Effect Estimation: Doubly Robust Regression Model

To estimate the effects of attending 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 et al., 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. $$ln\left(\frac{p_{ij}}{1-p_{ij}}\right) = \beta_{0j} + \beta_{1j}T_{ij} + \beta_{3j}X_{ij},$$

where p_{ij} is the probability of graduation 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 enrolled in a network school in the fall of Grade 9. The main parameter of interest is β_{1j}, which is the effect of attending the network school instead of the matched non-network school in a given school pair.

Subgroup Analysis

We also examined whether the effect of network school attendance on on-time high school graduation differed across the following subgroups:

- Gender: male versus female
- Free or reduced-price lunch status (FRPL): eligible versus not eligible[5]
- Prior ELA achievement: higher achieving versus lower achieving

We used two different approaches to create subgroups based on prior ELA achievement. First, we compared students' Grade 8 ELA test scores to the state average[6] 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 average and higher achieving if their score was above the state average. Second, we calculated the average Grade 8 ELA test score within each school pair and classified students as lower achieving if their test score fell below the pair-specific average and higher achieving if their score was above the average. The first definition compares students' test scores to a

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

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

statewide benchmark, whereas the second definition compares students' test scores to the test scores of their peers within the same school pair.

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., the 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.[7] 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 graduation) and subgroup analyses (which examine whether the effect of attending a network school differed across student subgroups). For the main analyses, the coefficients for the network school indicator were meta-analyzed; for the subgroup analyses, the coefficients for the interaction term between the network school indicator and the subgroup membership indicator were meta-analyzed. In both cases, the meta-analysis was based on the following equation:

Equation 5. $$\overline{ES} = \frac{\sum_{j=1}^{14} w_j\widehat{\beta}_j}{\sum_{j=1}^{14} w_j},$$

where $\widehat{\beta_J}$ 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.

[7] 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.

C. Results

Exhibit 2 presents the effect of attending the deeper learning network school on high school graduation for each pair of schools as well as the average effect across pairs based on a meta-analysis.

Exhibit 2. Treatment Effects on On-Time and Five-Year High School Graduation, by School Pair

School Pair	Effect on On-Time Graduation (odds ratio)	Effect on Five-Year Graduation (odds ratio)
Meta-Analytic Average	1.396*	1.357*
Pair 1	1.032	0.952
Pair 2	1.974*	1.612
Pair 3	2.014	6.598
Pair 4	3.358*	3.493*
Pair 6	0.908	9.808
Pair 7	1.085	0.963
Pair 8	1.876*	2.219*
Pair 9	1.275	1.213
Pair 10	0.725	0.802
Pair 11	2.893*	2.740*
Pair 12	0.862	0.849
Pair 13	1.922*	1.855*
Pair 14	1.212	1.214
Pair 15	1.201	1.157

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

Exhibit 3 presents the results of the subgroup analysis for on-time high school graduation. Specifically, Exhibit 3 contains coefficients for the interaction term in Equation 4, which represents the extent to which the effect of attending a network school on on-time high school graduation differed between students who qualified for FRPL and students who did not. We did not find significant average differential effects based on students' gender or prior ELA achievement.

In the brief, we presented (1) the actual graduation rates for students who were eligible for FRPL and students who were not eligible in network schools and (2) the estimated graduation rates for the two student subgroups in non-network schools. Relying on district administrative data, the actual graduation rates for network school students were computed by dividing the number of network school students who graduated from high school within four years by the total number of network school students (separately for each student subgroup). Estimated graduation 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 were not eligible for FRPL (subgroup = 0) in each pair. Results from the subgroup analysis also allowed us to compute the effect for students who were eligible for free and reduced-price lunch (subgroup = 1) in each pair, which is the sum of the coefficient for the indicator of attending a network school and the coefficient for the interaction term.[8] Using meta-analyses, we computed the average effect across pairs for each of the two student subgroups. For each student subgroup, the estimated graduation rate for non-network school students was then calculated by (1) converting the graduation rate for network school students in the subgroup into logits, (2) subtracting the average treatment effect (in logits) for the subgroup from the graduation rate (in logits) for the network school students, and (3) converting the difference (in logits) back to a predicted probability of on-time high school graduation.

Exhibit 3. Differential Effect on On-Time High School Graduation by Students' Eligibility for Free- or Reduced-Price Lunch, by School Pair

School Pair	Differential Effect (odds ratio)
Meta-Analytic Average	0.712*
Pair 1	1.019
Pair 2	0.356*
Pair 3	N/A
Pair 4	N/A
Pair 6	N/A
Pair 7	N/A
Pair 8	0.530
Pair 9	0.660
Pair 10	0.799
Pair 11	1.082
Pair 12	N/A
Pair 13	0.567
Pair 14	1.344
Pair 15	0.433*

Note: * indicates that the odds ratio is significant at the .05 significance level. N/A denotes that data for free and reduced-price lunch status was not provided by the district for students in the school pair.

[8] 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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