The Promotion Power Impacts of Louisiana High Schools

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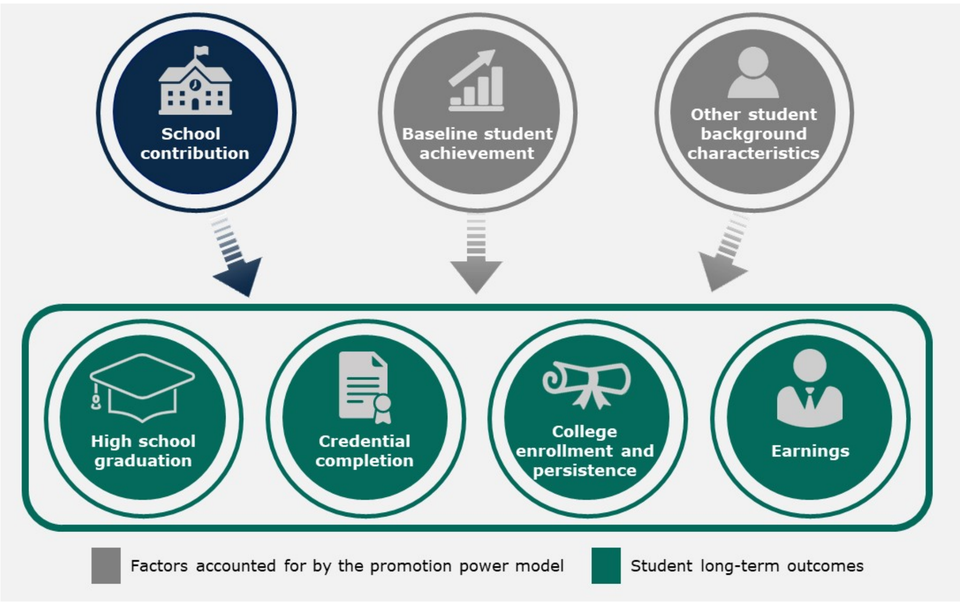
Executive Summary
The Promotion Power Impacts of Louisiana High Schools

Key Takeaways

In partnership with the Louisiana Department of Education (LDOE), and through a grant from the Walton Family Foundation, Mathematica has developed measures of each Louisiana public high school's *promotion power*—the school's impact on the long-term success of its students, as indicated by high school graduation, college or career readiness, college enrollment and persistence, and success in the job market. These new measures will enable Louisiana to become one of the first states to report on high schools' success in *improving* the prospects for their students in higher education and the workforce.

Measures of promotion power aim to fairly compare schools serving different populations of students. The measures are based on statistical models that identify schools' contributions to students' long-term outcomes separately from other factors, such as prior achievement and demographic characteristics (Figure ES.1). The statistical models are designed to create (to the extent possible) a level playing field that permits fair comparisons of schools that serve different student populations.

Figure ES.1. Promotion power measures separate schools' contributions to students' long-term outcomes from other factors



Measures of promotion power substantially reduce or even eliminate the relationship between student poverty and the school's measure of performance, thereby assessing school effectiveness more accurately. Student background characteristics and preparation before high school affect student success, so schools serving advantaged students tend to have better outcomes regardless of how well they are serving those students. For example, Louisiana high schools with low poverty rates—as measured by the percentage of students eligible for free or reduced-price lunches—tend to have higher college enrollment (Figure ES.2, left panel). In contrast, schools can do just as well in promotion power regardless of the economic advantages or disadvantages of students they serve (Figure ES.2, right panel).

TECHNICAL REPORT NOTES

This report includes details about the outcomes, data, and statistical model used to calculate the promotion power of Louisiana public high schools. The measures of student success we analyze include:

- Graduating high school on time
- Completion of a college or career readiness credential
- College enrollment
- Persisting in college
- Earnings at age 26

DATA

Student background and high school graduation data are from LDOE administrative records. College enrollment and persistence data come from the National Student Clearinghouse. Earnings data are from the Louisiana Workforce Commission. Section II.A contains details about data security procedures.

METHODS

To measure schools' promotion power, we used a statistical model to account for student test scores at the end of 8th grade as well as student demographic characteristics. Each measure of promotion power is based on data from two cohorts of students.

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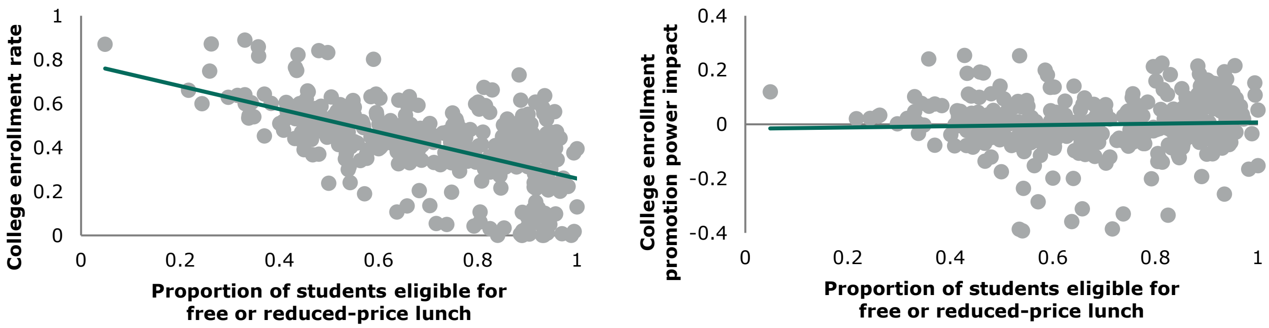
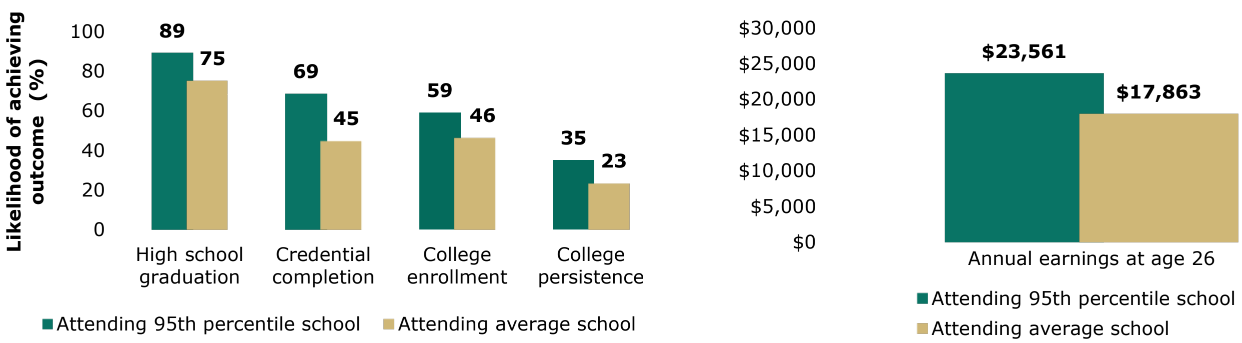
Figure ES.2. Schools with higher poverty rates have lower rates of college enrollment, but promotion power puts schools on a level playing field



Notes: Each dot represents a Louisiana high school. The green line indicates the relationship between the proportion of students eligible for free or reduced-price lunch and each school measure.

Louisiana high schools vary widely in their success in promoting high school graduation, college enrollment, and eventual earnings. The promotion power measures distinguish 41 to 67 percent of Louisiana high schools from average across outcomes. A typical student who moved from an average high school to one at the 95th percentile of each promotion power distribution could expect substantially better outcomes (Figure ES.3).

Figure ES.3. Expected outcomes of students attending high schools with high promotion power are substantially better than those of similar students attending high schools with average promotion power



Notes: Each set of bars depicted in this figure is based on a separate promotion power distribution and represents different schools. It is unlikely that a single school would be at the average or 95th percentile of all promotion power models.

Schools with a positive impact on one measure of promotion power are more likely to positively impact other student long-term outcomes, but many schools show varying effectiveness for different outcomes. Table ES.1 reports the correlations between measures of promotion power for each school across the outcomes included in our analysis. The correlations are positive and statistically significant across the majority of outcomes. For example, schools that successfully promote high school graduation also tend to promote college enrollment and earnings. Even so, some of the correlations are not very large: high schools that are particularly good at promoting college enrollment and persistence, for example, do not necessarily promote strong earnings for their students at age 26. This highlights the need to include multiple measures of promotion power to capture the different ways schools can influence student long-term outcomes.

Table ES.1. Promotion power impacts are positively correlated across outcomes

Outcome	Credential completion	College enrollment	College persistence	Earnings (age 26)
High school graduation	0.36	0.57	0.15	0.27
Credential completion	--	0.24	n/a	n/a
College enrollment	--	--	0.72	-0.07+
College persistence	--	--	--	-0.03+

Notes: The correlations in this table are based on the most recent available cohorts for each pair of outcomes. The correlations between credential completion, college persistence, and earnings are not reported because we do not have data for the same set of cohorts for those outcomes. All correlations are significantly different from zero at the 0.05 level, except those indicated by the + symbol.

n/a = not applicable.

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ACKNOWLEDGMENTS

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I. INTRODUCTION

The Louisiana Department of Education (LDOE) seeks to measure the *promotion power* of its high schools—the effectiveness of each high school in promoting the long-term success of its students—as indicated by high school graduation, completion of a college or career readiness credential, college enrollment and persistence, and ultimately earnings.

Several studies have shown that some high schools can have significant positive impacts on students' long-term outcomes. For example, some studies have found large effects of Catholic schools on high school and college graduation and future earnings (Neal 1997; Grogger and Neal 2000; Evans and Schwab 1995). Sass et al. (2016) and Booker et al. (2011) found significant impacts of charter high schools in Chicago and Florida on graduation, college attendance and persistence, and earnings in adulthood. Angrist et al. (2016) showed that Boston charter schools have positive impacts on postsecondary preparedness and the selectivity of colleges their students attend.

Though research has shown high schools can substantially influence students' long-term outcomes, few states report information that could be used to measure the effectiveness of high schools at improving these outcomes. Although some states report the college enrollment rate of high school graduates, almost no states currently report the *impacts* each high school has on college enrollment or other longer-term outcomes such as college persistence, and earnings (Achieve 2017).[1] The distinction between reporting the raw outcomes and the schools' impacts on those outcomes is critical, because the raw outcomes are affected by many factors that are outside the control of schools, such as the socioeconomic status and education levels of students' parents (Aldeman 2015). A simple comparison of the college enrollment rates of students from a high-income suburban high school and students from a low-income rural high school, for example, cannot tell us whether one school is doing better at *promoting* college enrollment for the students it serves.

With the adoption of promotion power measures, Louisiana will become one of the first states to measure and report how well each public high school is advancing its students' long-term success—levelling the playing field for high schools, regardless of the advantages and disadvantages of the students they serve. This will enable the state to identify high-performing high schools that can serve as exemplars of how to improve long-term outcomes for students, as well as low-performing high schools that might need help.

The promotion power measures described in this report are based on statistical models that account for student 8th-grade test scores and other background characteristics such as poverty status, disability, and 8th-grade attendance and suspensions. They are similar to value-added models of student test score growth commonly calculated for teachers and schools. Researchers have shown that teacher value-added models produce valid and reliable measures of teachers' impacts on growth in student test scores (Kane and Staiger 2008; Kane et al. 2013; Chetty et al. 2014a) and that these

[1] Kansas is the only state we are aware of that currently reports on a measure of high school student college enrollment and persistence that accounts for student background characteristics. More details about the measure Kansas uses is available at https://kasb.org/blog/ksde-measures-of-postsecondary/.

measures are related to student college and earnings outcomes (Chetty et al. 2014b). Similarly, researchers evaluating school value-added measures have found that they contain minimal bias (Deutsch 2012; Deming 2014), though the measures can be improved upon if data from school choice lotteries are available (Angrist et al. 2017).

We cannot be certain that the statistical adjustments in promotion power models succeed in making the playing field 100-percent level across high schools, because school choice lotteries have not yet been used to examine the causal validity of promotion power models. Even so, making statistical adjustments for important student characteristics (such as 8th-grade achievement) is likely to substantially improve on raw measures of student outcomes in assessing high schools' effectiveness.

Calculating promotion power measures can be thought of as a two-step process. In the first step, we use a statistical model to estimate the likelihood that each student would achieve a certain outcome, such as college enrollment, based on that student's background characteristics. In the second step, we compare the actual college enrollment rates of each high school to the expected rates based on the statistical model. The promotion power measure for college enrollment is the actual deviation above or below the expected college enrollment rate. The measure answers the following question: To what extent does the actual college enrollment rate of a high school's students exceed (or fall short of) the level that students with similar 8th-grade test scores and background characteristics would reach if they were taught by the average school in the state?

The next chapter provides details about the data sources for the outcomes included in the promotion power measures as well as the student background characteristics accounted for in the statistical models. Chapter III provides the technical details of the specification of the statistical models, and Chapter IV summarizes the resulting promotion power measures.

II. OUTCOMES AND BACKGROUND CHARACTERISTICS USED IN THE PROMOTION POWER MODELS

A. Outcomes analyzed in the promotion power models

This section briefly describes the outcomes used to measure high school promotion power. Appendix Section A contains additional details about the construction of each measure. Data from the Louisiana Workforce Commission (LWC) were handled in accordance with the measures outlined in the agreement between LWC and LDOE. Strict security measures are maintained for LWC data, such that only a small number of LDOE staff who have signed nondisclosure agreements can access them. Additionally, data from the National Student Clearinghouse (NSC) were handled in accordance with the measures outlined in the agreement between LDOE and NSC.

1. High school graduation

The first promotion power measure we analyzed is the impact schools have on the likelihood that students will graduate from high school on time. On-time high school graduation occurs when a student graduates within four years of the first time that student enrolled in a Louisiana public high school in 9th grade. If a student repeats 9th grade and does not catch up to the rest of his or her cohort within the next three years, that student is counted as not graduating high school on time. The two most recent cohorts of high school graduates with data available for our analysis graduated in spring 2016 and spring 2017.

Outcome: High school graduation

Definition: Graduating high school on time – within four years of the first time a student entered 9th grade

Data source: LDOE administrative data from the 2015–16 and 2016–17 school years

2. Completion of a college or career readiness credential

The next outcome used for promotion power measures whether students have completed a college or career readiness credential (or "credential completion" for short) by the time students graduate high school. Louisiana defines credential completion as either (1) completing college-level coursework by taking an Advanced Placement class, an International Baccalaureate course class, or a Dual Enrollment college class; or (2) demonstrating proficiency with an industry-valued skill set that is recognized by the Workforce Investment Council. Similar to the high school graduation outcome, the credential completion analysis includes students graduating in spring 2016 or spring 2017.

Outcome: Completion of a college or career readiness credential

Definition: Completing college-level coursework or demonstrating proficiency with an industry-valued skill set

Data source: LDOE administrative data from the 2015–16 and 2016–17 school years

3. College enrollment

We also use as an outcome whether students enroll in college in the fall following their expected high school graduation date. Enrollment in either a two-year or four-year college counts toward this measure. Data are from the NSC and based on college enrollment during fall of 2016 and the fall of 2017.

Outcome: College enrollment

Definition: Enrolling in a two-year or four-year college during the fall semester after a student's expected high school graduation date

Data source: NSC data from the 2016–17 and 2017-18 school years

4. Multi-year college persistence

Our ideal measure of college attainment for promotion calculations would be earning a bachelor's degree from a four-year college. Though the NSC tracks college graduation outcomes for students, institutions sometimes under-report degree completion (Dynarski et al. 2015). This issue is especially prevalent among Louisiana colleges in the NSC data; analyses by LDOE staff show that college graduation can be under-reported—or not reported at all—by certain colleges in some years. When we tested using NSC data on college graduation in promotion power models, the results tended to be statistically noisy and unreliable. We therefore recommend against including a measure of college graduation based on NSC data in the promotion power models. However, if LDOE were able to obtain graduation data from in-state public colleges from the Louisiana Board of Regents, that might be sufficient to supplement the NSC data and include college graduation as an outcome in future years.

Whereas graduation is poorly measured in the NSC data, several possible measures of persistence in college are well reported. To select one of these possible persistence measures, we examined the enrollment patterns of students who are reported as graduating in the NSC data (Appendix Section A). This analysis led us to the following measure of multi-year college persistence (referred to as "college persistence" for short): attending college for at least four years—at least two of which are at a four-year college—within five years of a student's expected high school graduation date. A small percentage of students did not satisfy these criteria but were classified as completing a four-year degree according to the NSC data; these students also counted toward this measure for calculating promotion power for college persistence.

The college persistence outcome uses earlier cohorts of Louisiana students than the college enrollment outcome, such that data from the NSC on the 2016–17 or 2017–18 school years would represent the fifth year after the cohorts were expected to graduate from high school. That is, the college enrollment outcomes use cohorts graduating high school in spring 2016 and spring 2017, whereas the college persistence outcome uses cohorts graduating in spring 2012 and spring 2013.

Outcome: Multi-year college persistence

Definition: Attending college for at least four years—at least two of which are at a four-year college—within five years of a student's expected high school graduation date

Data source: NSC data from the 2012–13 through 2017–18 school years

5. Earnings at age 26

The longest-term promotion power outcome measure we examined is earnings in Louisiana at age 26.[2] We chose age 26 for our analysis because it is the latest age for which data on Louisiana students are available, and it provides enough time for students who attended college to complete their undergraduate degree and start working.

The measure captures the amount a student earned during the calendar year eight years after the student's expected high school graduation date (the calendar year that students in this cohort turn 26), through an employer that reports earnings to Louisiana's unemployment insurance system. Louisiana students who end up working out of state, join the military, or are self-employed do not appear in the unemployment insurance data and are therefore classified as having zero earnings according to this measure.

Because students who attend college out of state might be more likely to work out of state after college, we excluded from the analysis the 3 percent of students who attend an out-of-state college and do not appear as employed in Louisiana in any available year of earnings data. We also compared this main measure of promotion power to measures based on two alternative approaches:
(1) including these students in the analysis and counting them as having zero earnings, and
(2) excluding all students who never appear as employed in Louisiana in any available year—representing 24 percent of students. The results of these comparisons are described in Appendix Section D.

Data for this analysis are based on quarterly earnings records from the LWC for calendar years 2014 and 2015, which are the most recent years of data LDOE staff currently have access to. The annual earnings measure is a sum of earnings in the four quarters of each calendar year. To limit the influence of outlier earnings observations, we top-coded annual earnings at $105,000.[3] Less than 1

[2] We also examined an indicator for being employed (having non-zero earnings) at age 26, as a possible additional promotion power outcome. However, we found that this outcome did not vary substantially across schools and that the promotion power measure based on it was not likely to provide meaningful information about school effectiveness.

[3] Top-coding is a commonly used approach to handle outlier earnings observations (for example, Couch and Placzek 2010; Chetty et al. 2014b).

percent of annual earnings observations included in our analysis were initially greater than $105,000 and were top-coded.

Outcome: Earnings at age 26

Definition: Annual earnings reported to Louisiana's unemployment insurance system during the calendar year that students in this cohort turn 26

Data source: Quarterly earnings data from the LWC from 2014 and 2015

6. *Outcome summary statistics*

Table II.1 displays averages and standard deviations for each outcome used in the promotion power models. Approximately three-quarters of students graduate high school on time, almost half enroll in college, and a little less than one-quarter persist for multiple years in college. The average earnings amount might appear low because unemployed individuals are counted as having $0 earnings in this calculation. Among individuals with positive earnings, the average annual amount is $26,114. All of these measures show substantial variation among high schools across the state.

Table II.1. Outcome summary statistics

Variable	Average (percentage or dollars)	Across-school standard deviation (percentage points or dollars)	Number of students	Number of high schools
High school graduation	75.0	30.4	89,351	352
Credential completion	44.7	24.7	89,351	352
College enrollment	46.2	21.8	89,351	352
College persistence	23.3	18.5	84,561	375
Annual earnings at age 26	$17,863	$5,412	81,778	377

Notes: Outcome summary statistics are based on the two most recent years of available data, which are 2015–16 and 2016–17 for the high school graduation outcome, 2016–17 and 2017–18 for college outcomes, and 2014 and 2015 for earnings. All students who enrolled in a Louisiana high school in 9th grade and have non-missing data on the necessary outcomes and background characteristics are included in the sample. The number of students and schools in the college persistence row is different from that in the college enrollment row, because it is based on earlier cohorts of students. The high school graduation, credential completion, and college enrollment rates will not exactly match those reported on LDOE's website due to differences in which cohorts are included in the calculations and how the measures are constructed. Appendix Section A contains additional details.

B. Background characteristics used as control variables in the promotion power models

The promotion power models include as control variables 8th-grade test scores and multiple other background characteristics for students. These account for the fact that high schools serve different populations of students who might be more or less likely to succeed on the outcomes described in the previous section, regardless of which high school they attend.

The background characteristics are listed in Table II.2, along with a brief description of each variable. All characteristics come from LDOE administrative data. Appendix Section B contains summary statistics and additional details about the construction of each measure. Appendix Section G reports the coefficients on each background characteristic variable in the promotion power models.

Many value-added models of teacher and school effectiveness include race/ethnicity and gender as control variables (for example, Gonzalez et al. 2016; Chetty et al. 2014a; Walsh et al. 2014), while others exclude these variables (for example, Florida Department of Education 2015; Resch and Deutsch 2015; Isenberg and Walsh 2014). LDOE requested that we not use indicators for these characteristics in the promotion power models, for consistency with LDOE's school and teacher value-added models.

In Appendix Section D, we report results from a robustness check where we added indicators for race/ethnicity to the model. The correlations with the main results ranged from 0.91 to 0.98, depending on the outcome. The correlations were lowest for the college enrollment and persistence outcomes, indicating a stronger relationship between race/ethnicity and college outcomes than for high school graduation, after accounting for the other control variables included in the models. In another robustness check in which we added an indicator for gender, all of the correlations were 0.99 and above.

Table II.2. Background characteristics included in promotion power models

Variable	Description
8th-grade test scores	Louisiana Educational Assessment Program (LEAP) scores in English language arts, math, science, and social studies taken during the spring of each student's 8th-grade year
8th-grade absences	The number of days a student was absent from school in 8th grade. We create an annualized measure of absences for students who were present in the district for less than the full year (see Appendix Section B for details).
8th-grade suspensions	The number of days a student received an in-school or out-of-school suspension in 8th grade. We create an annualized measure of suspensions for students who were present in the district for less than the full year (see Appendix Section B for details).
Attended 8th grade fewer than 45 days	Because the number of absences and suspensions rates for students who attended 8th grade for fewer than 45 days are based on a small sample of days and likely to be unreliable, we treated the 8th-grade suspension and absence rates for these students as missing data and used this indicator to account for them.
Over-age for grade	An indicator for whether the student is two or more years over-age (16 or older) as of October 1st of their 9th-grade year
Transfer high schools	An indicator for whether the student transferred schools at some point during the student's high school career

Variable	Description
Disability status	Indicators for the following disability categories: Emotional Disturbance, Specific Learning Disability, Mild Intellectual Disability, Other Health Impairment, Speech or Language Impairment, and Other Disability
Gifted status	Indicator for whether the student was classified as gifted and talented
Limited English proficiency	Indicator for whether the student was classified as having limited proficiency in English
Free lunch receipt	Indicator for whether the student was eligible to receive free lunches
Reduced-price lunch receipt	Indicator for whether the student was eligible to receive reduced-price lunches

Note: All of the characteristics described in this table use data from 8th grade, except for the indicator for students who transfer high schools and the over-age indicator (see Appendix Section B for details).

III. TECHNICAL DETAILS FOR THE PROMOTION POWER MODEL SPECIFICATIONS

A. General description of promotion power models

The promotion power models are designed to measure the effectiveness of each high school in helping its students achieve the outcome of interest, after accounting for student background characteristics. The models generate a relative measure for each school that quantifies the difference between its students' outcomes and the expected outcomes if those students attended the average high school in Louisiana. By controlling for student characteristics, the models seek to distinguish the effects of high schools from other factors influencing student outcomes that are outside the control of schools.

Calculating the promotion power measure can be thought of as a two-step process. In the first step, we use a statistical model to estimate the likelihood that each student would achieve a certain outcome, such as college enrollment, based on that student's background characteristics. In the second step, we compare the actual college enrollment rates of each high school to the expected rates based on the statistical model. The promotion power measure for college enrollment is the deviation above or below the expected college enrollment rate. The measure answers the following question: To what extent does the actual college enrollment rate of a high school's students exceed (or fall short of) the level that students with similar 8th-grade test scores and background characteristics would reach if they were taught by the average school in the state?

To implement the calculation, we estimated a regression model that performs both of these steps simultaneously. We then accounted for measurement error in the resulting promotion power measures by adjusting schools' estimates toward the average, depending on the precision of the estimate for each school. Finally, we averaged school estimates over two consecutive cohorts. The rest of this chapter discusses each stage of the estimation process in detail.

B. Equations used for promotion power calculations

1. Description of the regression model

For each outcome, we estimated separate regressions for each cohort of students. Students are assigned to a cohort based on the first year they attended 9th grade. That is, if a student began 9th grade in fall 2014, and then was still in 9th grade in fall 2015 (because the student did not have enough credits to proceed to 10th grade), the student would be assigned to the 2014 cohort for the purpose of the promotion power models. As such, each student is assigned to only one cohort. The regression models take the following form:

(1) $Y_{it} = B_{it}\alpha_t + X_{it}\gamma_t + D_{it}\delta_t + e_{it}$

where, Y_{it} is the outcome variable for student i in cohort t; B_{it} represents a vector of students' baseline 8th-grade Louisiana Educational Assessment Program (LEAP) scores. X_{it} is the set of other student background characteristics listed in Table II.2; and D_{it} is the set of variables, one for each school, equal to 1 if student i attended that school, and equal to 0 otherwise. δ_t is a vector containing, for each school, the estimated effect of attending that school. The t subscripts indicate that the model is estimated separately for each cohort.

This regression model is analogous to the fixed effects model that has been used widely in the literature to estimate effectiveness of schools and teachers. In the context of teacher value-added models, Guarino et al. (2015)—who refer to this model as "dynamic ordinary least squares"—have found that this model is robust to a variety of assumptions.

2. *Linear probability model used to calculate most promotion power measures*

All of the outcomes we analyzed except for earnings are binary: they only take the values of 0 or 1. Some researchers use non-linear regression models, such as logistic or probit models, for binary outcomes. We used the linear probability model, which essentially treats the binary outcome as if it were continuous, for several reasons:

a. The coefficients from linear probability models are easy to interpret. The coefficient for a given school from the high school graduation model, for example, is the effect of attending that high school on the probability of graduating high school, in percentage points. Logistic models, on the other hand, generate coefficients in the form of log odds ratios, which are more challenging to interpret.

b. The linear probability model can estimate effects for all school–cohort combinations, including those in which all students have the same value for an outcome. Logistic models cannot estimate an effect for schools in which, for example, all of the students or none of the students graduate high school. Because many schools have relatively small cohorts of students, there are a non-trivial number of schools in which all students have the same value for the outcome.[4]

c. The linear probability model has generally been found to have good properties and to produce similar results to non-linear models in many settings (Wooldridge 2013).

As a robustness check, we estimated the promotion power models via logistic regression and compared the results to those from the main model. Because the logistic regression drops schools and their students when it cannot estimate an effect for them (see Part b above), we first limited the estimation sample for the main model to only those students and schools used in the logistic regression for the purpose of this comparison. The correlation between the main results and the results from the logistic regression ranged from 0.85 to 0.98 across outcomes (see Table A.2 in Appendix Section D).

[4] Though not as prevalent as with a logistic model, there are some schools where all students have the same outcome about which the linear probability model does not provide useful information. See Appendix Section C for additional details.

3. *Data on students who attend multiple high schools are weighted according to the time spent at each school*

To account for many students attending more than one school in their high school careers, we created distinct observations for each student–school combination and used weighted least squares so that each student contributes the same total weight. That is, a student who spent one-quarter of his or her high school career at school A and three-quarters at school B would contribute two records to the data: the first would be assigned a weight of 0.25 student equivalents toward school A's total and the latter a weight of 0.75 student equivalents toward school B's total.[5] This technique, referred to as the Full-Roster Method, was introduced by Hock and Isenberg (2017) as a way to account for students who are taught by multiple teachers in the same year and subject in value-added models. It has also been used to account for students who attend multiple schools in school value-added models (Resch and Deutsch 2015; Gonzalez et al. 2019; Walsh et al. 2019). As recommended by Hock and Isenberg (2017), we used cluster-robust standard errors to account for the correlation between multiple observations of the same student.

To avoid generating imprecise estimates based on small samples of students, we required each school to have at least 10 student equivalents in the cohort to be included in the model. To avoid dropping students at schools that do not meet this requirement from the analysis, we reassigned the weight for these students to a single outside school record. Less than 1 percent of student-equivalent weight is assigned to the outside school record for each outcome.

Students who do not spend 9th grade in a Louisiana public high school and transfer in at a later grade are excluded from the promotion power calculations. The majority of these students are missing information on 8th-grade test scores, meaning that we do not have sufficient information about their background before they enter high school to fairly compare them to other students in the analysis. Some students might spend 8th grade in Louisiana, transfer out of Louisiana public schools in 9th grade, and return at a later grade before finishing high school. These students are also excluded from the analysis, because they did not spend 9th grade in a Louisiana high school and were therefore not taught by Louisiana public schools for a duration comparable to other students.

4. *Two cohorts of students are used for each measure to increase precision*

The precision of promotion power estimates increases as the number of students included in the calculations for each school increases. To gain greater precision for the promotion power estimates, LDOE requested that we combine two cohorts when calculating each school's promotion power measures. Table A.4 in Appendix Section E shows how the measures become more precise as multiple cohorts of students are combined. Precision increases substantially when two cohorts are used instead of one, but less so when the number of cohorts is increased to three, which helped inform LDOE's decision to use two cohorts.

One downside to combining estimates in this way is that the information used for promotion power measures becomes less current as the data go back one year further. However, given that promotion

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[5] See Appendix Section C for further details.

power measures are already long-term measures of outcomes occurring years after students began attending high school, the increase in precision might outweigh the drawback of the data being less current by one year.

To combine the estimates, we generated a weighted average of each school's estimates for the two cohorts, in proportion to the number of student equivalents in each cohort for that school. That is, if a school has 50 student equivalents in one cohort and 100 in another, the first would receive a weight of 1/3, while the latter would receive a weight of 2/3. When calculating the standard error of the combined estimate, we again weighted by student equivalents and treated the two estimates as independent because they are based on different sets of students in each cohort. As with all averages of independent estimates, the standard error of the combined (averaged) estimate is lower than the standard errors of each one separately.

5. Empirical Bayes shrinkage is applied to enhance the stability of the measures

Even after restricting the analysis to schools with at least 10 student equivalents, it would still be the case that, by random chance, smaller schools would be more likely to have promotion power estimates far from the mean than larger schools. To address this issue, we employed empirical Bayes shrinkage following the procedure described by Morris (1983). This procedure moves school estimates toward the mean in proportion to their precision. That is, a school with fewer students, and thus less precision, will be "shrunk" toward the mean more than a school with more students. The theory behind this approach is that each school is assumed to be average until proven otherwise; the more precise the information is that the school is different from average, the less weight we place on the assumption that the school is average. An empirical Bayes shrinkage adjustment is commonly used in value-added models (for example, Angrist et al. 2017; Chetty et al. 2014a; Kane and Staiger 2008). Appendix Section C provides additional details.

6. Students with some missing background characteristic data are included in the model

Students' 8th-grade LEAP scores are important control variables in our model, as they measure students' academic achievement just before entering high school. As such, we excluded from the model students who have no 8th-grade test score records, either because they did not attend a Louisiana school in 8th grade or for some other reason. Less than 5 percent of students had at least one of the four test scores from 8th grade (math, English language arts [ELA], social studies, or science), but were missing one or more of the other scores. To accommodate these students, we included indicators, one for each subject, for students who were missing an 8th-grade test score, and set scores for these students to the state average.

For students who were enrolled in a Louisiana school for fewer than 45 days in 8th grade, we treated their annualized 8th-grade absence and suspension days as being missing, so as not to use noisy extrapolations of what their rates would have been in a full year of school. Similar to the approach for missing LEAP scores described above, we set the 8th-grade attendance and suspension days for these students to a constant and included an indicator for being enrolled fewer than 45 days in 8th grade.

To confirm that the promotion power measures are not sensitive to these modeling decisions, we estimated models that exclude any student who is missing any 8th-grade test score or was enrolled for fewer than 45 days in 8th grade. For each outcome, the correlation between the promotion power measures from the main model and the alternative model was greater than 0.99 (see Table A.2 in Appendix Section D).

7. Limitations

Two key limitations are important to note regarding the promotion power measures. One is that by examining high school effects on long-term outcomes, the time of outcome measurement is necessarily far removed from the time that students were in high school. Even though high school graduation is measured at the end of high school, and college enrollment shortly thereafter, the school factors that contribute to these outcomes begin as early as 9th grade. For example, a student who does not graduate on time may have started to fall behind in his or her courses and disengage from school in 9th grade, and would not contribute to his or her school's promotion power measure until four years later. This presents a limitation in that the promotion power measures reflect school practices from years earlier. Because schools might improve or decline in effectiveness over time, a school's most recent reported promotion power measure might not reflect its current effectiveness.

Second, although the literature has generally found school value-added measures to be accurate, no studies have examined the accuracy and validity of promotion power measures on long-term outcomes. There could be reasons that value-added measures estimating growth in a single year on test score outcomes could be accurate while promotion power measures on long-term outcomes might be less so. For one, prior-year test scores could be more effective control variables for current-year test scores than 8th-grade test scores are for long-term outcomes. More generally, factors outside of the school's control might exist, such as the level of parental involvement, that influence long-term outcomes but we do not capture in our data. These factors might be correlated with which school a student attends and could play a more prominent role in influencing long-term outcomes than they do for current-year test scores.

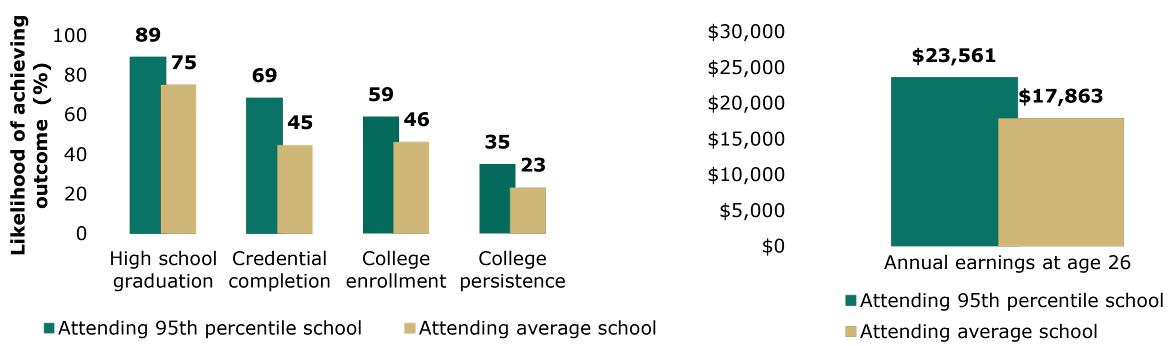
Even though school promotion power measures are imperfect, they account for key characteristics outside schools' control and thus can do much better than raw outcome measures at identifying schools' impacts on those outcomes.

IV. RESULTS OF PROMOTION POWER MODELS

We present a number of ways of examining the promotion power results. First, we report the extent to which promotion power is detecting meaningful differences across schools. We look at the difference between a school at the 95th percentile in the promotion power distribution for a given outcome relative to the average high school in Louisiana. This value represents the degree to which a typical student's probability of attaining the outcome (graduating high school, enrolling in college, and so forth) would increase if the student moved from an average school to a school at the 95th percentile in promotion power for that outcome (Figure IV.1). Note that each set of bars depicted in Figure IV.1 is based on a separate promotion power distribution and represents different schools. It is unlikely that a single school would be at the average or 95th percentile of all promotion power models.

For the latest cohorts available for each outcome, we found that students moving from an average to a 95th percentile school for each outcome would have their likelihood of (1) graduating from high school increase by 14 percentage points, (2) completing a college or career readiness credential increase by 24 percentage points, (3) enrolling in college increase by 13 percentage points, and (4) persisting in college increase by 12 percentage points. The earnings at age 26 of a student moving from the average school to the 95th percentile school for earnings promotion power would increase by $5,698.

Figure IV.1. Expected outcomes of students attending high schools with high promotion power are substantially better than those of similar students attending high schools with average promotion power



Notes: Each set of bars depicted in this figure is based on a separate promotion power distribution and represents different schools. It is unlikely that a single school would be at the average or 95th percentile of all promotion power models.

The difference in impact between the 95th percentile and average Louisiana high school on the promotion power measures is large, and within the range of impact estimates found in other studies. Catholic high schools have been found to increase high school graduation rates for urban minorities by 16 to 18 percentage points (Neal 1997; Grogger and Neal 2000). Another study found that the offer of a DC Opportunity Scholarship increased student high school graduation rates by 12 percentage points (Wolf et al. 2010). After a school reform effort in New York City, newly created small high schools of choice increased high school graduation rates by 9 percentage points and college enrollment by 8 percentage points (Bloom and Unterman 2014). Dobbie and Fryer (2015) showed that students who win an admissions lottery at a high-performing charter middle/high school in New York City were 13 percentage points more likely to graduate from high school and 17 percentage points more likely to enroll in college immediately after graduating. Similarly, Davis and Heller (2019) found that winning an admissions lottery to a high-performing charter high school in Chicago increased college enrollment and persistence by 10 percentage points. Sass et al. (2016) showed that attending charter high schools in Florida increased high school graduation rates by 6 percentage points, college attendance rates by 9 percentage points, college persistence rates by 12 percentage points, and annual earnings from ages 23 to 25 by $2,300.[6]

Another way to measure the extent to which the promotion power measures distinguish between schools is to examine the proportion of schools that are statistically distinguishable from average. We found that 53 percent of schools are statistically distinguishable from average based on promotion power for high school graduation, 67 percent for credential completion, 41 percent for college enrollment, 47 percent for college persistence, and 44 percent for earnings at age 26 (Table IV.1). The average standard error, a measure of the precision of the typical school's promotion power estimate, ranges from 3 to 4 percentage points across the binary outcomes and is $1,456 for the earnings outcome.

Table IV.1. Precision and magnitude of the promotion power measures

	Outcome				
Measure	**High school graduation**	**Credential completion**	**College enrollment**	**College persistence**	**Earnings (age 26)**
Percentage of schools different from average	52.8	67.3	40.6	46.7	44.0
Average standard error (percentage points or dollars)	2.7	3.0	3.1	2.6	$1,456
Standard deviation (percentage points or dollars)	10.4	13.4	7.2	6.2	$3,248
Standard deviation (standard deviation units)	0.24	0.27	0.14	0.15	0.15
R-squared	0.27	0.31	0.24	0.24	0.09

The third row of Table IV.1 displays the standard deviation of the promotion power impacts, which is a measure of how large the difference is between the effectiveness of high- and low-performing schools in terms of their ability to influence student outcomes. For example, students attending a high school that is one standard deviation above average in the promotion power distribution for

[6] Most of the studies cited here report impacts that average over multiple schools. Analyzing a single very high-performing school, such as the 95th percentile example used in our results, would likely lead to larger estimated impacts.

college enrollment are 7 percentage points more likely to enroll in college than students attending an average school.

Because the outcomes used for promotion power are from distributions with different student-level standard deviations, and because earnings are measured in units different from the other outcomes, the magnitude of the values in the third row of Table IV.1 are not directly comparable to each other. In the fourth row of Table IV.1 we report the same measures as in the third row, except we convert them to student-level standard deviation units so that they are all on the same scale. This conversion highlights that there is a larger spread among high schools' impacts on high school graduation and credential completion than there is on the college and earnings outcomes, presumably because the college and earnings outcomes occur later in life when high schools are no longer directly influencing student outcomes. The standard deviations of the promotion power measures for college enrollment, college persistence, and earnings are comparable to the standard deviation of school test score value-added typically reported in the literature (Gonzalez et al. 2016; Deming 2014), while those for high school graduation and credential completion are larger. However, it is important to note that promotion power measures capture a high school's influence on students over the course of four years, whereas school test score value-added typically measures a school's impact on one year of achievement growth.

The school impacts and student background characteristics included in the promotion power models for high school and college outcomes explain 24 to 31 percent of the variation in student outcomes, as measured by the R-squared values of the regressions. This is substantially less than the R-squared values typically found in the value-added literature, which often report values from 0.60 to 0.80 (see Walsh et al. 2018; Gonzalez et al. 2015). The higher R-squared values in other studies are likely in part due to use of a lagged version of the outcome (student test scores) as a control variable, which is not possible in promotion power measures (because 8th graders do not have prior measures of graduation, college enrollment, or earnings).

The lower R-squared values for the promotion power models could indicate that these measures are less successful in removing bias than typical value-added measures, if some of the unexplained variation is due to unobservable student characteristics that are correlated with the schools that students attend. However, the R-squared values for the promotion power models for high school and college outcomes are also lower because of the binary nature of the outcomes. R-squared values are expected to be lower in regression models with binary outcomes than in similar models with continuous outcomes, because the model cannot possibly explain as much of the variation in the binary outcome (Cox and Wermuth 1992).

The R-squared value of the promotion power model for earnings is the lowest among the outcomes we analyzed. The school impacts and student background characteristics explain 9 percent of the variation in earnings at age 26. This could be because this outcome is measured eight years after high school completion; because there can be substantial year-to-year fluctuations in earnings; or because the earnings advantage associated with higher education might not be fully evident until later than age 26.

Promotion power measures are stable over time. The performance of a high school is unlikely to change rapidly from one year to the next, so promotion power measures should be relatively stable. The year-to-year correlations of the main promotion power measures are reported in the first row of Table IV.2. Stability of the measures is quite high, partly by construction: one year of data overlaps in each two-year window used to calculate the correlation. But even when we examine results (in the second row of Table IV.2) for single years (which are non-overlapping), correlations remain high and range from 0.63 to 0.73.

Table IV.2. Promotion power measures are stable over time

	Outcome				
Measure	**High school graduation**	**Credential Completion**	**College enrollment**	**College persistence**	**Earnings (age 26)**
Year-to-year correlation of main two-year measure	0.91	n/a	0.86	0.88	n/a
Year-to-year correlation of single-year measure	0.73	0.69	0.63	0.68	0.66

Notes: The high school graduation and college enrollment correlations are based on 12 years of data while the college persistence correlation is based on 8 years of data. Only 2 years of data were available for the credential completion and earnings measures, which is why it was not possible to calculate a year-to-year correlation of the two-year measure for those outcomes.

n/a = not applicable.

Schools with a positive impact on one promotion power measure are more likely to positively impact other student long-term outcomes, but many schools show varying effectiveness for different outcomes. Table IV.3 reports the correlations between promotion power measures for each school across the outcomes included in our analysis. In this table, we used the same two cohorts of students for each measure from the most recently available years, in order to isolate the relationship in school impacts across measures from potential changes in a school's impact over time.[7] This means that the correlations between high school graduation, credential completion, and college enrollment use the cohorts of students who graduated high school in 2016 and 2017, the correlations involving the earnings outcome uses the cohorts graduating in 2006 and 2007, and the correlations involving college persistence use the cohorts of students graduating in 2012 and 2013 (except for the correlation between college persistence and earnings, which uses the cohorts graduating in 2006 and 2007).

[7] The use of the same sets of cohorts for each pair of correlations in Table IV.3 could result in correlations that are biased upwards if there are student-specific shocks that are positively correlated across outcomes. As a robustness check, we calculate a similar set of correlations using adjacent cohorts for each pair of outcomes. The results were generally lower than those reported in Table IV.3, which could in part be due to true changes in school effectiveness over time when adjacent cohorts are used. All the correlations that were statistically significant when overlapping cohorts were used remained statistically significant when adjacent cohorts were used (Appendix Table A.3).

Table IV.3. Promotion power impacts are positively correlated across outcomes

Outcome	Credential completion	College enrollment	College persistence	Earnings (age 26)
High school graduation	0.36	0.57	0.15+	0.27
Credential completion	--	0.24	n/a	n/a
College enrollment	--	--	0.72	-0.07+
College persistence	--	--	--	-0.03+

Notes: The correlations in this table are based on the most recent available cohorts for each pair of outcomes. The correlations between credential completion, college persistence, and earnings are not reported because we do not have data for the same set of cohorts for those outcomes. All correlations are significantly different from zero at the 0.05 level, except those indicated by the + symbol.

n/a = not applicable.

Data on credential completion were only available for the two most recent years, so we did not have overlapping cohorts between credential completion and the persistence and earnings measures. For the closest available cohort (which was four years apart) the correlation between credential completion and college persistence was 0.02 and not statistically significant. The correlation between credential completion and earnings for the closest available cohort was 0.14 and statistically significant, despite the fact that the cohorts were 10 years apart and the effectiveness of schools may have changed over that time period.

For the majority of promotion power measures, the correlations across measures are positive and statistically significant. For example, schools that positively impact students' likelihood of graduating from high school positively impact the credential completion, college enrollment, and earnings outcomes for these students as well. However, even for the correlations that are statistically significant, the fact that some are substantially less than 1 suggest that some schools are relatively better at helping students graduate from high school than they are at improving other outcomes. This highlights the need to include multiple promotion power measures to capture the different ways schools can influence student long-term outcomes.

The low correlations between the promotion power measures for earnings at age 26 and the corresponding measures for college enrollment and persistence might be driven by three factors. First, some high schools might focus more on improving the earnings of their students than they are on college outcomes. For example, a recent study of high schools in Connecticut focused on career and technical education (CTE) found that they had positive impacts on the outcomes related to high school graduation and earnings at age 23 for male students, but negative impacts on the college enrollment outcomes of those students—presumably because they were effectively preparing their students for jobs that did not require college (Brunner et al. 2019).

Second, the college earnings premium increases with age—it might be that age 26 is too early for a high school's impact on college enrollment and completion to be reflected in a student's long-term earnings (Card and Lemieux 2001). Third, college enrollment and persistence have much smaller impacts on a student's future wages than college degree completion (Jaeger and Page 1996). As discussed previously, we would like to include college degree completion as an outcome for promotion power, but we are unable to do so because of the under-reporting of degree completion in the NSC data. Appendix Section F shows differences in earnings at age 26 for students with varying levels of educational attainment to help explain the low correlations with the college enrollment and persistence measures, and why we might expect to see a substantially higher correlation if we could calculate a promotion power measure for college degree completion.

Though there is a low correlation between the promotion power measures for college enrollment and persistence and earnings at age 26, both sets of measures might provide useful information about high school impacts on student outcomes. A school's impact on enrollment and persistence might not translate directly to an impact on early-career wages, but the completion of some college without a degree has been shown to boost later-career wages after individuals have had a chance to gain work experience (Jaeger and Page 1996; Kane and Rouse 1995). In addition, college enrollment and persistence are necessary steps students must take to complete a degree, so in the absence of a promotion power measure for degree completion, these measures provide important indications of a school's likely impact on degree completion.

Similarly, promotion power impacts on earnings at age 26 might contain additional important information about a school's impact beyond what the other measure are able to provide. If some high schools are especially good at preparing students for jobs that do not require college (like the CTE schools in Connecticut), the earnings measure should provide evidence of that. And if some high schools are especially good at preparing students for college graduation (which we cannot directly observe without an accurate measure of degree completion), the earnings measure should provide some evidence of that as well.

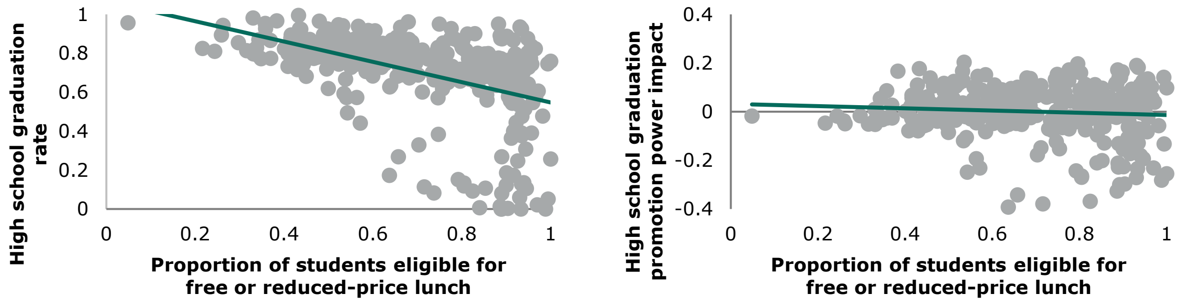
Compared to school average outcomes, promotion power measures are much less strongly related to student background characteristics. One of the central goals of promotion power measures is to remove the bias that exists when using school average outcomes as measures of school effectiveness. In other words, we aim to account for and remove the effect of differences in student advantages and disadvantages that are not under the control of schools. We examine this by showing how the relationship between school average baseline characteristics and the measure of effectiveness change if we use school average outcomes, as opposed to promotion power, as a measure of effectiveness. That is, we expect that school-level baseline characteristics will drive some of the variation in school average outcomes, but they should not drive as much of the variation in promotion power.[8]

The left panels of Figures IV.2 through IV.6 show the relationship between school poverty rates—as measured by the percentage of students eligible for free or reduced-price lunches (FRL)— and the raw outcome measures, whereas the right panels show the relationship between the school poverty rates and the schools' promotion power measures. School average levels of high school graduation, credential completion, college enrollment, college persistence, and earnings are strongly negatively related to the proportion of students eligible for FRL at the school, consistent with decades of research. However, when looking at promotion power measures in place of the unadjusted rates, one

[8] We do not necessarily expect school average baseline characteristics and promotion power measures to be completely uncorrelated, even if the promotion power measures are unbiased. For example, students from low-income households (as measured by eligibility for FRL) might attend schools that are truly less effective than schools serving students from higher-income households.

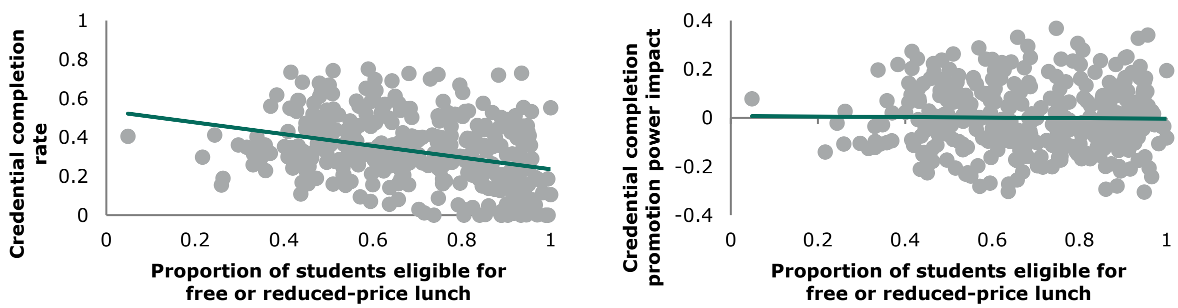
finds that the negative relationship is substantially reduced for high school graduation; disappears for credential completion, college enrollment, and earnings; and becomes slightly positive for college persistence. This suggests that the promotion power measures are much more effective than raw outcome measures at putting all high schools on a level playing field and isolating their impacts on their students, regardless of the advantages or disadvantages those students might bring with them.

Figure IV.2. Large negative relationship between high school graduation rates and school poverty, but no relationship for promotion power impacts



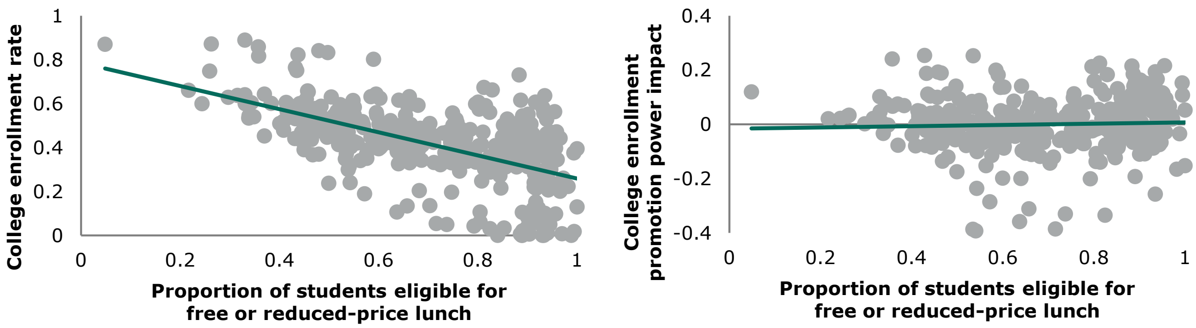
Notes: Each dot represents a Louisiana high school. The green line indicates the relationship between the proportion of students eligible for free or reduced-price lunch and each school measure. The slope of the regression line in the graph on the left is negative and statistically significant at the 0.05 level; the slope of the regression line in the graph on the right is not significantly different from zero.

Figure IV.3. Large negative relationship between credential completion rates and school poverty, but no relationship for promotion power impacts



Notes: Each dot represents a Louisiana high school. The green line indicates the relationship between the proportion of students eligible for free or reduced-price lunch and each school measure. The slope of the regression line in the graph on the left is negative and statistically significant at the 0.05 level; the slope of the regression line in the graph on the right is not significantly different from zero.

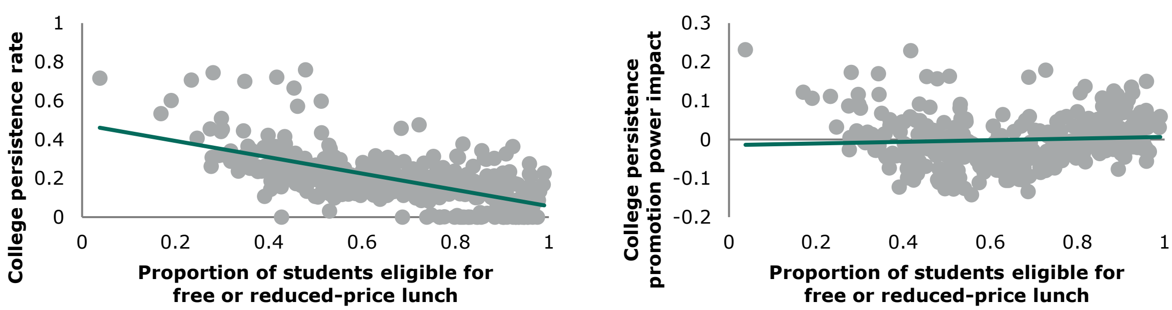
Figure IV.4. Large negative relationship between college enrollment rates and school poverty, but small positive relationship for promotion power impacts



Notes: Each dot represents a Louisiana high school. The green line indicates the relationship between the proportion of students eligible for free or reduced-price lunch and each school measure. The slope of the regression line in the graph on the left is negative and statistically significant at the 0.05 level; the slope of the regression line in the graph on the right is positive and statistically significant.

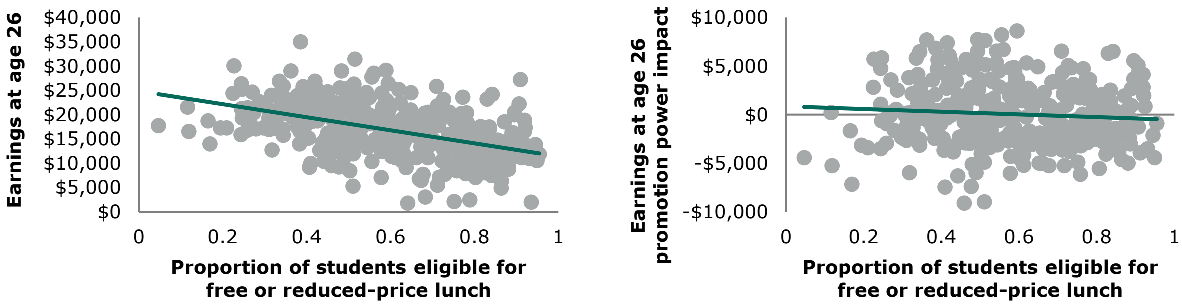
The positive relationship in the right panel of Figure IV.4 indicates that schools with higher proportions of students eligible for FRL have slightly higher promotion power impacts for college enrollment compared to schools with lower proportions of FRL-eligible students. Though this relationship is statistically significant, it is relatively small in magnitude. A 10 percentage point increase in the percentage of students eligible for FRL is associated with a 0.4 percentage point increase in the promotion power measure for college enrollment.

Figure IV.5. Large negative relationship between college persistence rates and school poverty, but no relationship for promotion power impacts



Notes: Each dot represents a Louisiana high school. The green line indicates the relationship between the proportion of students eligible for free or reduced-price lunch and each school measure. The slope of the regression line in the graph on the left is negative and statistically significant at the 0.05 level; the slope of the regression line in the graph on the right is not significantly different from zero.

Figure IV.6. Large negative relationship between earnings and school poverty, but no relationship for promotion power impacts



Notes: Each dot represents a Louisiana high school. The green line indicates the relationship between the proportion of students eligible for free or reduced-price lunch and each school measure. The slope of the regression line in the graph on the left is negative and statistically significant at the 0.05 level; the slope of the regression line in the graph on the right is not significantly different from zero.

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APPENDIX

A. Additional details about outcome measures

High school graduation. We measured graduation as a traditional high school diploma from a public Louisiana high school. Similar to the definition of graduation used for LDOE's school accountability system, students who drop out of high school to complete a General Education Degree, or transfer out of Louisiana public schools to a private school or a school in another state, are counted as not graduating from high school for the purposes of the promotion power analysis.

The high school graduation rate in this report differs from the one reported by LDOE because two cohorts of students are used for our promotion power model, whereas LDOE reports single-year graduation rates.

Credential completion. Though students might complete the courses necessary to earn a credential before graduating high school, this outcome is measured at the time of high school graduation such that all students who do not graduate from high school on time are also not counted as completing a credential.

Similar to the high school graduation outcome, the credential completion rate in this report differs from the one reported by LDOE because two cohorts of students are used for our promotion power model, whereas LDOE reports single-year credential completion rates.

College enrollment. LDOE obtains college enrollment data from the NSC by sending a list of student names and birth dates to the NSC to be matched with its college data obtained from participating institutions. Nearly all public and private nonprofit colleges, and a majority of for-profit colleges, report data to the NSC, such that the NSC data cover 97 percent of college students (NSC 2019). For this outcome, we included enrollment that occurred from August to December of the academic year following the spring the student was expected to graduate from high school.

We also explored using a college enrollment outcome based on whether the student attended college in either of the first two academic years following the spring the student was expected to graduate from high school. We estimated the correlation between school promotion power estimates on college enrollment using these two versions of the outcome, and found a correlation of 0.97. Because the two measures produce very similar results, we recommend using the measure based on only one academic year because the promotion power results would be available one year closer to the time when students were in high school.

LDOE only sends data from students who graduate from high school to the NSC for matching purposes, meaning that students who are not counted as graduating from high school in the promotion power models are assumed not to enroll in college within one year of their expected high school graduation date.

A small number of students were recorded as graduating from high school but their data were not sent to the NSC for matching purposes, and thus could not have been recorded as attending college. These students were dropped from all models.

The college enrollment rate in this report differs from the one reported by LDOE because the college enrollment rate we report is a percentage of all students who enrolled in Louisiana high schools in 9th grade, whereas the college enrollment rate reported by LDOE is a percentage of students who graduated from high school.

College persistence. LDOE and other researchers (Dynarski et al. 2015) have found that the NSC measure of college graduation is incomplete. Because the NSC's main objective is to determine whether a given student is enrolled in college at a given point in time, the data are inconsistent in capturing whether a student earned a degree. As a result, while students who were recorded as graduating in the NSC data can be assumed to have actually graduated, a student who actually graduated may or may not be recorded as having done so in the data. We therefore constructed the outcome measure for multi-year college persistence to capture college completion as closely as the data would allow.

Because students who were recorded as graduating from a four-year college can be considered true graduates, we examined the college-going patterns of these students to develop our measure of persistence that would approximate college degree completion. Generally, these students completed at least four years of college in total, and at least two of those years were at a four-year college. We ultimately built the measure of multi-year college persistence that counts students as persisting if they attended college for at least four years, at least two of which were at a four-year college. The small percentage of students who we did not observe persisting for at least four years but who received a bachelor's degree in the NSC data also counted toward this persistence measure.

National data indicate that earning a bachelor's degree takes more than four years for over half of college students (Woo et al. 2012), which indicates that we should wait more than four years to evaluate whether students have completed a bachelor's degree. On the other hand, if we examined our measure too many years after a given cohort was expected to graduate high school, it would increase the time between when promotion power is measured and when that cohort attended high school. To balance the priorities of accurately approximating college completion with limiting the time between when the outcome is measured and when students attended high school, we measured multi-year college persistence using the five years after a student's cohort was expected to graduate high school.

Earnings. Data on all 9th- through 12th-grade students enrolled in Louisiana public high schools during the years 2005–06 through 2014–15 were sent to the LWC to be matched to unemployment insurance records for calendar years 2013–2015. Matching was done based on student Social Security number (SSN). LDOE stopped collecting data on student SSNs in recent years, and is currently in discussion with the LWC about obtaining earnings data in subsequent years using alternative matching methods. Data on all students in our analysis sample were sent to the LWC for matching with two exceptions: (1) those with missing or inaccurate SSNs were not sent to the LWC, and (2) LDOE recently restructured its student ID system, which resulted in some students in historical years not being assigned student IDs. In total, less than 2 percent of students in our analysis sample were excluded from the promotion power models for earnings because their data were not sent to the LWC for matching.

B. Additional details about background characteristics

With the exception of whether students transferred between high schools and the over-age for grade variable, all data are measured during the year the student was in 8th grade.

8th-grade test scores. To account for changes in score scaling and content across years, we standardized the LEAP test scores in ELA, math, science, and social studies separately by subject and year to have a mean of 0 and standard deviation of 1 before using the scores to calculate promotion power. We used the most recent test score for students who repeated 8th grade.

8th-grade attendance and suspensions. The models use a measure of 8th-grade attendance based on the annualized number of absences a student had in 8th grade. That is, if a student attended 8th grade for only half the year (90 school days) and was absent for 10 of those days, his or her annualized absences would be set to 20 (based on a 180-day school year). We also top-coded annualized absences at 60 to reduce the influence of outliers.

Suspensions are based on the total number of in-school and out-of-school suspensions students received in 8th grade. We annualized suspensions in a similar way as absences and top-coded the annualized number of suspensions at 18 to reduce the influence of outliers.

Transfer high schools. School transfers can be disruptive to students' high school academic achievement and could lead to worse long-term outcomes. Ideally, if students transfer out of schools because the schools are negatively impacting their long-term outcomes, we would attribute this transfer behavior to the low-performing high schools themselves and not include an indicator for it. However, because the majority of student transfers likely occur for reasons outside the control of schools (Rumberger 2015), we chose to include a transfer indicator in the promotion power models. Including this indicator prevents schools that receive large numbers of transfer students from experiencing negative impacts in their promotion power scores as a result.

Free or reduced-price lunches. For all the promotion power models described in this report, we used indicators for FRL eligibility as a measure of poverty level. Starting in 2014, Louisiana switched from using FRL status as a measure of student poverty to an indicator of economic disadvantage. Students are considered economically disadvantaged if they are eligible for the Supplemental Nutrition Assistance Program, Temporary Assistance for Needy Families, or Medicaid; receive free or reduced-price lunch; or are categorized as limited English proficient, homeless, migrant, in foster care, or incarcerated. In future years, promotion power models will use the economic disadvantage indicator in place of FRL status.

Disability variables. The promotion power models for cohorts graduating from 2010 onward include indicators for six disability categories: Emotional Disturbance, Learning Disability, Intellectual Disability, Other Health Impairment, Speech Impairment, and other disability. These variables were not available for prior cohorts, so we instead used an indicator for whether the student received special education services (and an indicator for the students in these cohorts for whom special education information missing).

Table A.1 displays averages and across-school standard deviations for each background characteristic used as a control variable in the promotion power models.

Table A.1. Summary statistics of background characteristics

Variable	Average	Across-school standard deviation
LEAP ELA standardized score	0.08	0.57
LEAP math standardized score	0.07	0.50
LEAP science standardized score	0.07	0.54
LEAP social studies standardized score	0.07	0.51
Missing LEAP ELA score	0.3%	2.4 pp
Missing LEAP math score	0.5%	2.5 pp
Missing LEAP science score	0.5%	2.3 pp
Missing LEAP social studies score	0.7%	4.5 pp
8th-grade absences: Annualized	8.8 days	4.9 days
Over-age for grade	8.1%	16.5 pp
Transfer high schools	21.3%	32.8 pp
Free lunch receipt	57.0%	23.4 pp
Reduced-price lunch receipt	7.9%	9.4 pp
Limited English proficiency	1.2%	1.9 pp
8th-grade suspensions: Annualized	0.6 days	1.0 days
Disability: Emotional Disturbance	0.2%	5.5 pp
Disability: Learning Disability	2.8%	9.6 pp
Disability: Intellectual Disability	0.1%	0.8 pp
Disability: Other Health Impairment	1.3%	6.1 pp
Disability: Speech Impairment	1.0%	1.6 pp
Other disability	0.6%	7.9 pp
Gifted status	3.7%	5.3 pp
Attend 8th grade fewer than 45 days	0.3%	1.4 pp

Notes: Summary statistics of background characteristics are based on data from the two cohorts of students entering the 2015–16 and 2016–17 high school graduation promotion power models. These students were in 9th grade during the 2012–13 and 2013–14 school years.

pp = percentage points.

C. Additional model details

Shrinkage procedure. To accommodate that we are combining estimates across years, we first shrunk each cohort-specific estimate for each school, then combined the two shrunk estimates across two cohorts. We adopted this approach, rather than first combining and then shrinking, to allow for the reporting of single-year measures that can be averaged together to produce the main two-year measures. However, without further adjustment this would result in estimates that are moved toward the mean by too much: the precision for the single-cohort estimates, which informs how much shrinkage should be induced, is much less than the precision of the combined estimates that use two cohorts. Thus, we applied an adjustment by scaling the estimated variance of the cohort-specific estimates by 1/2, applying shrinkage based on this reduced variance, then scaling the variance of the shrunk estimate by 2. We then combined these adjusted estimates and variances as described above.

Setting the sum of the weights equal to 1 for all students. We set the total weight, across all observations for a student, to 1. This means that a student who attended all four years at a high school contributes the same weight to that high school as a student who attended in 9th grade and then left Louisiana public schools or dropped out. We chose to do this because we cannot distinguish students who drop out of high school from those who leave state public schools. Because dropping out is related to the outcome of graduating in four years (as well as later outcomes), reducing the contributions of students based, in part, on their outcome would introduce bias into the promotion power measures.

Addressing out-of-range expected outcomes. For the credential completion and college outcomes, there are some cases where zero percent of students at a school achieve a given outcome. Because we are using a linear probability model, it is possible for the regression model to produce an expected outcome rate of less than zero percent for these schools. We removed these schools from the results distribution, because the model is not able to provide useful information about a school's impact on the outcomes of its students in such cases. Less than 1 percent of schools in the credential completion model and college enrollment models, and 7 percent of schools in the college persistence model were removed as a result of this restriction.

D. Robustness checks

We made a number of data and modeling decisions when developing the promotion power measures. To check the sensitivity of the results to these decisions, we estimated a number of alternative models as robustness checks.[9] We measured the sensitivity of the results by correlating estimates of school promotion power from the main model with those from each alternative model. A high correlation indicates that we would obtain similar estimates if we used the alternative model, so the main model is robust to the data or modeling decision in question; a lower correlation suggests that the decision has a more substantive influence on the results. The results of the robustness checks are displayed in Appendix Table A.2. The correlations range from 0.85 to >0.99, which is consistent with other studies comparing the sensitivity of value-added model results to different modeling decisions (Guarino et al. 2015; Johnson et al. 2015; Goldhaber et al. 2013).

Logistic regression. Our main model uses a linear probability model, as discussed in Chapter III, Section 4, though it is also common to use logistic regression when the outcome variable is binary. For this robustness check, we estimated a logistic regression. The logistic regression automatically drops high schools that have no variation in the outcome from the estimation sample, along with all of their students. To measure the extent of differences for a consistent set of schools, for the purpose of this robustness check we estimated a linear probability model using only those schools and students that were kept in the logistic regression. The correlations range from 0.85 to 0.98.

Excluding students with missing test scores and background characteristics. In our main model, we included students who are missing one or more LEAP test scores (math, ELA, social studies, and

[9] Fewer robustness checks are performed for the earnings results because they are substantially more time consuming due to the security measures governing access to those data.

science) as long as they are not missing all scores and include students who have unreliable data on 8th-grade absence rates and suspensions due to being enrolled in Louisiana schools for fewer than 45 school days. In this robustness check, we instead excluded these students from the sample. Correlations exceed 0.99 in all cases.

Cubic specification pre-test scores. In our main model, we assumed a linear relationship between each of the pre-test scores and the outcome. We did not use a polynomial specification both for simplicity and because research has shown that polynomial specifications of prior test scores can exacerbate problems related to test score measurement error (Lockwood and McCaffrey 2014). However, polynomial functions of prior test scores are frequently used in the literature (for example, Chetty et al. 2014a; Mansfield 2015; Jackson 2014), and it is possible the true relationship between long-term outcomes and 8th-grade test scores is non-linear. Therefore, as a robustness check, we allowed the relationship for each pre-test score to be cubic.

The correlations between the main model and the specification with cubic prior test scores are all at least 0.99.

Including gender and race/ethnicity variables. In our main model, we did not use indicators for students' gender or race/ethnicity for consistency with the school and teacher value-added models LDOE uses. However, many value-added models of teacher and school effectiveness include these characteristics (for example, Gonzalez et al. 2016; Chetty et al. 2014a; Walsh et al. 2014). In these robustness checks, we added indicators for race/ethnicity and gender, along with an indicator for students who were missing data on gender. For the model that includes race/ethnicity variables, the correlations ranged from 0.91 to >0.99. They were lowest for the college enrollment and persistence outcomes, indicating a stronger relationship between race/ethnicity and college outcomes than for high school graduation, after accounting for the other control variables included in the models. For the model that includes gender, all of the correlations were at least 0.99.

Table A.2. Correlations between results from robustness check models and the main model

Outcome	Logistic regression	Polynomial 8th-grade test scores	No missing baseline covariates	Add race covariates	Add gender covariates
High school graduation	0.98	>0.99	>0.99	0.98	>0.99
Credential completion	0.92	>0.99	>0.99	>0.99	>0.99
College enrollment	0.92	>0.99	>0.99	0.91	>0.99
College persistence	0.85	0.99	>0.99	0.93	0.99

Alternate promotion power models for earnings. In the main model, we exclude students who attended an out-of-state college and did not appear in the earnings data. As robustness checks, we also estimated models in which we (1) included all students whose data were sent to the LWC for matching, and (2) excluded all students who did not appear in the earnings data. When we included all students, the correlation of promotion power impacts with those from the main model was 0.99. When we excluded all students with no earnings data, the correlation was 0.93.

Correlations across outcomes using adjacent cohorts. The results reported in Table IV.3 use the same sets of cohorts for each pair of correlations, which could result in correlations that are biased upwards if there are student-specific shocks that are positively correlated across outcomes. As a robustness check, we calculated a similar set of correlations using adjacent cohorts for each pair of outcomes. For example, for the correlation between promotion power measures for high school graduation and credential completion, we used the high school graduation measure based on the cohorts that graduated in 2016 and 2017 and the credential completion measure based on the cohorts that graduated in 2014 and 2015.

Using adjacent cohorts, rather than the same cohorts, generated correlations that are generally lower, as expected (Table A.3). The lower correlations are likely caused by two factors: (1) using adjacent cohorts avoids contamination from student-specific shocks that are positively correlated across outcomes, and (2) high school's effectiveness changes over time (as demonstrated in the second row of Table IV.2), and the adjacent cohorts are as far as three years apart.

Table A.3. The correlations across promotion power measures are similar when adjacent cohorts are used

Outcome	Credential completion	College enrollment	College persistence	Earnings (age 26)
High school graduation	0.26	0.44	0.19	0.26
Credential completion	--	0.11	n/a	n/a
College enrollment	--	--	0.60	–0.05+
College persistence	--	--	--	–0.05+

Notes: The correlations in this table are based on the most recent available adjacent cohorts for each pair of outcomes. The correlations between credential completion, college persistence, and earnings are not reported because we do not have data for adjacent cohorts for those outcomes. All correlations are significantly different from zero except those indicated by the + symbol.

n/a = not applicable.

E. Precision increases as cohorts are added

Chapter III, Section B.4, discusses how the precision of school estimates changes as additional cohorts are included in the measure. Using additional cohorts of students increases precision, and it adds a year between the time the measure can be estimated and when the students included in the model were in high school. In addition, the benefit in precision decreases as cohorts are added: the gain in precision is greater when going from one cohort to two cohorts than when increasing from two cohorts to three. Our main model balances the advantages and disadvantages of additional cohorts by using two cohorts for each measure. Table A.4 shows how the proportion of schools significantly different from average increases, and the average standard error generally decreases, as we add cohorts.

Table A.4. The precision of the promotion power measures increases with the number of cohorts used in the calculations

	High school graduation			Credential completion			College enrollment			College persistence		
Number of cohorts	**1**	**2**	**3**	**1**	**2**	**3**	**1**	**2**	**3**	**1**	**2**	**3**
Proportion statistically different from average (%)	41.4	52.8	57.0	60.1	67.3	n/a	27.4	40.6	44.4	33.0	46.7	47.5
Average standard error (percentage points)	3.5	2.7	2.5	4.1	3.0	n/a	3.8	3.1	2.7	3.2	2.6	2.7

n/a = not applicable.

F. Earnings premiums by educational attainment

As discussed in Chapter IV and illustrated in Table IV.3, we found no correlation between the promotion power measures for college enrollment and persistence and the promotion power measure for earnings. This finding is unexpected: if a school is better than average at getting its students to attend and persist in college, and those outcomes lead to higher earnings, we would expect these same high schools to be better than average at promoting earnings. To explore this finding in more detail, we examined differences in earnings by levels of secondary and postsecondary educational attainment, often referred to as earnings premiums.[10]

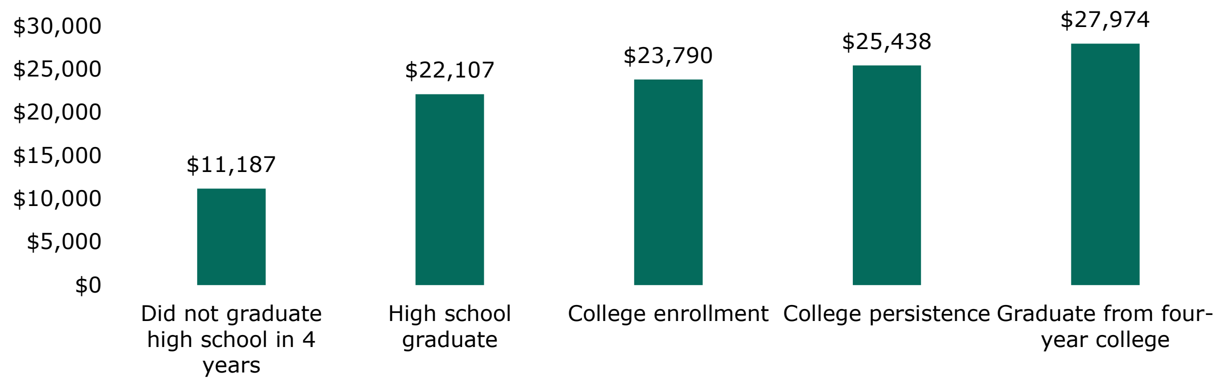
We start by presenting two figures that show the earnings data behave as one would expect, in that average earnings increase with education level and the earnings premium associated with college enrollment increases with age. We then show in a third figure that, after accounting for the variables included in the promotion power models, the earnings premium at age 26 associated with college

[10] For analyzing these premiums, we examined students who graduated from a four-year college, according to the NSC, within six years of when they should have graduated from high school. However, the NSC does not capture college graduation data for all students, so we could not use this outcome as a promotion power measure, as it would have underestimated promotion power for high schools that might have many graduates attending colleges that did not report graduation data to the NSC (Chapter II, Section A.4, provides additional details).

enrollment and persistence are lower than the premium associated with high school graduation, which helps explain the low correlations between those promotion power measures and the promotion power measures for earnings.

First, earnings at age 26 increase as educational attainment increases, and the biggest difference is between students who did not graduate high school and those who have (Figure A.1).

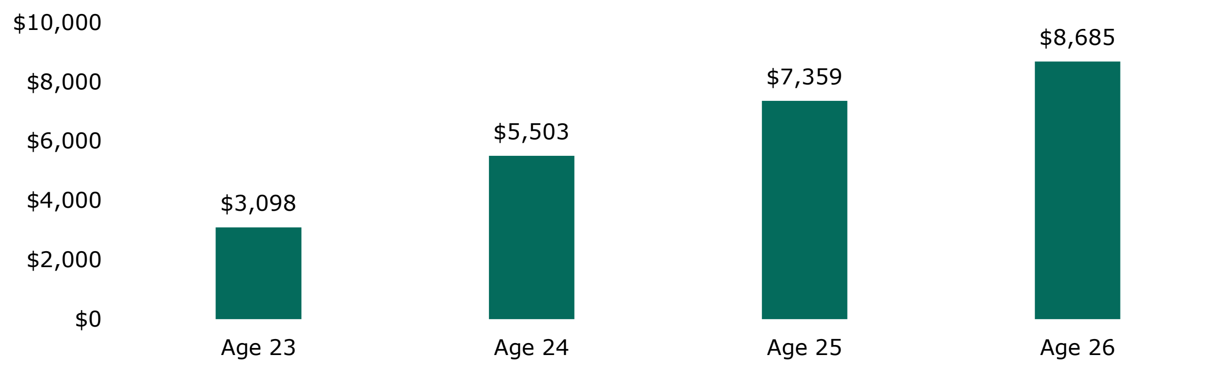
Figure A.1. Average earnings at age 26 increase with educational attainment



Notes: For each category other than students who did not graduate from high school in four years, all students who reached at least that level of educational attainment are included. For example, the high school graduate category includes students who went on to enroll in college, persist in college, and so on.

Second, the earnings premiums in Figure A.1 are likely to grow as the students age. As an example, we show that the premium for enrolling in college increases from age 23 to age 26, suggesting it is likely to continue to grow with age (Figure A.2).

Figure A.2. The earnings premium for college enrollment increases with age

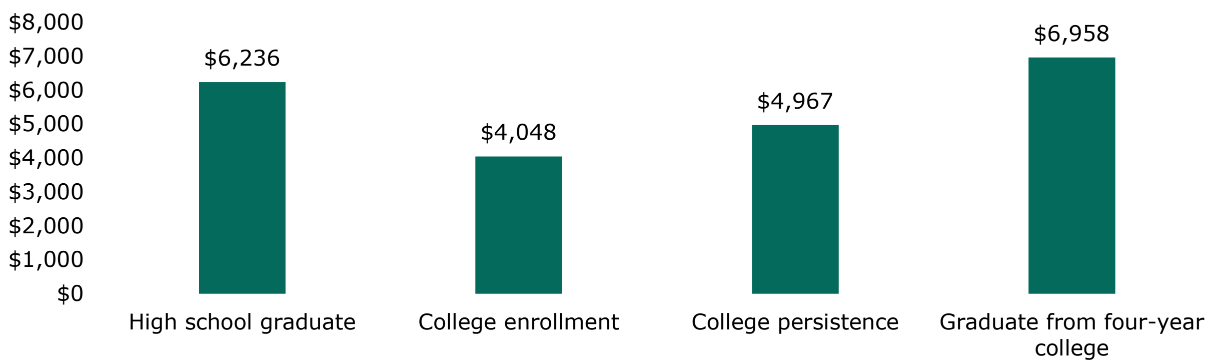


Notes: The premium for college enrollment is the difference in earnings between all those students who enrolled in college in the fall of the year they should have graduated from high school (which includes those who went on to persist in college and/or graduate) and all those students who did not enroll (which includes students who graduated from high school and those who did not).

Finally, the sizes of adjusted earnings premiums for different categories help explain the pattern of correlations across promotion power measures discussed in Chapter IV. To more closely match the promotion power measures, we calculated adjusted premiums associated with each secondary and postsecondary educational attainment outcome. To calculate the adjusted premium, we regressed earnings at age 26 on an indicator for achieving the specified educational attainment and included all of the student characteristics in the promotion power models (8th-grade test scores, student absences, and so on). We ran this regression separately for each educational attainment outcome. The coefficient on the educational attainment indicator is the adjusted premium.

The adjusted premiums are highest for high school graduation and four-year college degree attainment and are lower for college enrollment and persistence (Figure A.3). This finding is in line with the patterns we observe in the correlations in Table IV.3, where the promotion power measure for high school graduation has a significant positive correlation with the promotion power measure for earnings, while the promotion power measures for college enrollment and persistence have a low correlation with the promotion power measure for earnings. The high adjusted premium for four-year college degree completion suggests that if Louisiana were able to capture this outcome for all students and we could calculate a promotion power measure for degree completion, the resulting measure would also be significantly positively correlated with earnings at age 26.

Figure A.3. Adjusted premiums are highest for high school graduation and four-year college degree completion



Notes: The premium for each category is the difference in earnings between all those students who achieved at least that level of graduation and all those students who did not, after controlling for background characteristics. For example, the college persistence premium is the difference in earnings between all students who persisted in college (including those who went on to graduate), and those who did not (including those who did not graduate high school, graduated high school, or enrolled in college).

G. Coefficients on background characteristic variables

Table A.5 lists the coefficients, standard errors, and significance levels for all of the test scores and student background characteristics used in the promotion power models, separately for each outcome.

Interpreting multivariate regression results. The coefficients displayed below might not reflect the relationship we would have observed if the other characteristics had not been accounted for in the model. Multiple regression coefficients can produce counterintuitive relationships between characteristics and the outcome in cases where the contribution of one characteristic is largely accounted for by a different characteristic in the model (Isenberg and Walsh 2014). For example, the coefficients on limited English proficiency status would likely be negative and larger in magnitude if the model did not also account for students' 8th-grade test scores, because students with limited English proficiency tend to have lower 8th-grade test scores.

Table A.5. Regression coefficients, standard errors, and significance levels for each model, by outcome

Background characteristic	High school graduation	Credential completion	College enrollment	College persistence	Earnings at age 26
LEAP ELA score	0.041***	0.078***	0.089***	0.068***	-1428.29***
	(0.003)	(0.004)	(0.004)	(0.003)	(213.07)
LEAP math score	0.036***	0.070***	0.063***	0.072***	2924.21***
	(0.003)	(0.003)	(0.003)	(0.003)	(200.61)
LEAP science score	-0.011***	0.024***	-0.016***	-0.006	988.11***
	(0.003)	(0.004)	(0.004)	(0.004)	(221.61)
LEAP social studies score	0.026***	0.039***	0.026***	0.037***	683.82**
	(0.003)	(0.004)	(0.004)	(0.003)	(216.26)
Missing LEAP ELA score	-0.088	-0.187***	-0.219***	-0.048	-221.69
	(0.045)	(0.038)	(0.033)	(0.041)	(916.89)
Missing LEAP math score	-0.064*	-0.004	-0.011	0.019	-4293.85***
	(0.031)	(0.026)	(0.028)	(0.036)	(1109.47)
Missing LEAP science score	0.084*	0.082**	0.085**	0.067**	292.85
	(0.033)	(0.030)	(0.028)	(0.024)	(1213.59)
Missing LEAP social studies score	-0.076**	0.054*	0.058*	0.042*	40.00
	(0.027)	(0.022)	(0.023)	(0.017)	(1137.88)
8th-grade absences: Annualized	-0.010***	-0.005***	-0.007***	-0.004***	-172.51***
	(0.000)	(0.000)	(0.000)	(0.000)	(9.83)
Over-age for grade	-0.243***	-0.097***	-0.147***	-0.040***	-668.12*
	(0.009)	(0.007)	(0.007)	(0.004)	(333.80)
Transfer high schools	-0.108***	-0.100***	-0.119***	-0.075***	-1893.80***
	(0.006)	(0.005)	(0.006)	(0.004)	(238.51)
Free lunch receipt	-0.032***	-0.080***	-0.097***	-0.080***	-3612.66***
	(0.004)	(0.005)	(0.005)	(0.005)	(239.15)
Reduced-price lunch receipt	-0.011	-0.045***	-0.071***	-0.058***	-2010.43***
	(0.007)	(0.008)	(0.008)	(0.007)	(385.96)
Limited English proficiency	0.006	0.133***	-0.009	0.037*	-3952.53**
	(0.017)	(0.018)	(0.018)	(0.015)	(1255.30)
8th-grade suspensions: Annualized	-0.029***	-0.018***	-0.018***	-0.010***	-490.23***
	(0.001)	(0.001)	(0.001)	(0.001)	(68.30)

Background characteristic	High school graduation	Credential completion	College enrollment	College persistence	Earnings at age 26
Gifted status	-0.028***	0.057***	0.035***	0.069***	-2854.38***
	(0.007)	(0.010)	(0.011)	(0.012)	(538.65)
Attend 8th grade fewer than 45 days	-0.311***	-0.198***	-0.204***	-0.077***	-4864.67*
	(0.043)	(0.039)	(0.040)	(0.022)	(1840.43)
Disability: Emotional Disturbance	-0.093*	-0.051	-0.067	-0.013	
	(0.043)	(0.035)	(0.037)	(0.018)	
Disability: Learning Disability	-0.004	-0.022	-0.050***	0.008	
	(0.013)	(0.012)	(0.012)	(0.006)	
Disability: Intellectual Disability	-0.131*	0.094	-0.017	0.129***	
	(0.066)	(0.056)	(0.056)	(0.035)	
Disability: Other Health Impairment	-0.028	-0.045**	-0.084***	-0.047***	
	(0.019)	(0.017)	(0.017)	(0.010)	
Disability: Speech Impairment	0.047**	0.016	0.030	-0.016	
	(0.018)	(0.021)	(0.022)	(0.015)	
Other disability	0.064*	-0.018	0.043	0.063*	
	(0.025)	(0.028)	(0.028)	(0.025)	
Special education					-1001.97*
					(403.40)
Special education missing					-2448.56*
					(945.36)
Number of students	44,760	44,760	44,760	42,681	41,137
R-squared	0.27	0.30	0.24	0.24	0.09

Note: Robust standard errors are in parentheses.

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

The coefficients, standard errors, and significance levels for the race/ethnicity and gender coefficients, estimated in separate robustness check models, are shown in Table A.6.

Table A.6. Regression coefficients, standard errors, and significance levels for race/ethnicity and gender for each model, by outcome

Variable	High school graduation	Credential completion	College enrollment	College persistence
Hispanic	-0.002	0.012	-0.032**	0.017
	(0.011)	(0.012)	(0.012)	(0.014)
American Indian/Alaska Native	0.020	-0.014	-0.023	0.014
	(0.015)	(0.019)	(0.019)	(0.021)
Asian/Pacific Islander	0.019	0.051***	0.077***	0.155***
	(0.013)	(0.015)	(0.017)	(0.019)
Black	0.092***	0.002	0.144***	0.108***
	(0.005)	(0.006)	(0.006)	(0.005)
Female	0.057***	0.089***	0.106***	0.107***
	(0.004)	(0.004)	(0.004)	(0.004)
Missing gender	-0.181**	-0.058	0.059	-0.043
	(0.066)	(0.049)	(0.067)	(0.066)
Number of students	44,760	44,760	44,760	42,681

Notes: The coefficients in this table were estimated in two separate models for each outcome. In one model, only the race/ethnicity variables were added; in another model, only the indicator for being female and the indicator for having missing data on gender were added. Robust standard errors are in parentheses.

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.