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Beyond College Rankings

A Value-Added Approach to Assessing Two- and Four-Year Schools

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Summary

The choice of whether and where to attend college is among the most important investment decisions individuals and families make, yet people know little about how institutions of higher learning compare along important dimensions of quality. This is especially true for the nearly 5,000 colleges granting credentials of two years or fewer, which together graduate nearly 2 million students annually, or about 39 percent of all postsecondary graduates. Moreover, popular rankings of college quality, such as those produced by *U.S. News*, *Forbes*, and *Money*, focus only on a small fraction of the nation's four-year colleges and tend to reward highly selective institutions over those that contribute the most to student success.

Drawing on a variety of government and private data sources, this report presents a provisional analysis of college value-added with respect to the economic success of the college's graduates, measured by the incomes graduates earn, the occupations in which they work, and their loan repayment rates. This is not an attempt to measure how much alumni earnings increase compared to forgoing a postsecondary education. Rather, as defined here, a college's value-added measures the difference between actual alumni outcomes (like salaries) and predicted outcomes for institutions with similar characteristics and students. Value-added, in this sense, captures the benefits that accrue from both measurable aspects of college quality, such as graduation rates and the market value of the skills a college teaches, as well as unmeasurable "x factors," like exceptional leadership or teaching, that contribute to student success.

While imperfect, the value-added measures introduced here improve on conventional rankings in several ways. They are available for a much larger number of postsecondary institutions; they focus on the factors that best predict objectively measured student economic outcomes; and their goal is to isolate the effect colleges themselves have on those outcomes, above and beyond what students' backgrounds would predict.

Using a variety of private and public data sources, this analysis finds that:

- Graduates of some colleges enjoy much more economic success than their characteristics at time of admission would suggest. Colleges with high value-added in terms of alumni earnings include not only nationally recognized universities such as Cal Tech, MIT, and Stanford, but also less well-known institutions such as Rose-Hulman Institute of Technology in Indiana, Colgate in upstate New York, and Carleton College in Minnesota. Two-year colleges with high-value added scores include the New Hampshire Technical Institute, Lee College near Houston, and Pearl River Community College in Mississippi.
- Five key college quality factors are strongly associated with more successful economic outcomes for alumni in terms of salary, occupational earnings power, and loan repayment:
  - ***Curriculum value:*** The amount earned by people in the workforce who hold degrees in a field of study offered by the college, averaged across all the degrees the college awards;
  - ***Alumni skills:*** The average labor market value, as determined by job openings, of skills listed on alumni resumes;

- *Completion rates:* The percentage of students finishing their award within at least twice the normal time (four years for a two-year college, eight years for a four-year college);
- ***Student aid:*** The average level of financial support given to students by the institution itself.

➤ Compared to conventional rankings, the college value-added measures developed in this report more accurately predict alumni economic outcomes for students with similar characteristics.

The findings here relating various quality measures to economic success are consistent with a growing body of evidence showing that policies and programs offered by colleges have important effects on the economic lives of students and surrounding communities. Specifically, financial aid and other less precisely measured student support programs can dramatically boost graduation rates and thus future student success. A college's curriculum, its mix of majors, and its provision of specific skills all strongly predict alumni earnings potential. College-specific data on these dimensions of quality can be used to learn about, evaluate, and improve college performance.

Measuring the economic value-added of colleges can provide valuable information to college administrators, students, families, and policy makers regarding critical public and private investment decisions. A steady annual inflow of high-earning graduates into state and local economies is a tremendous asset, boosting regional entrepreneurship and spending on housing and commerce, while elevating tax revenue. Officials can use these data as part of a broader strategy to motivate colleges to maximize alumni earnings, even for the least academically prepared students.

To be clear, this or other ratings systems should not serve as the sole criteria used by students or public officials to evaluate attendance or funding decisions, even on the narrow dimension of economic success. Rather, the data contained in this report (as well as more precise data from future research) should serve as a starting point for investigating a college's broad strengths and weaknesses with respect to career preparation. Further due diligence is required by trustees and public officials that oversee and finance colleges to assess the direction of the college, its current leadership, its role in the community, and other factors before using these data to guide policy. Likewise, students need to consider the college's economic outcomes against the net cost of attendance, scholarship opportunities, the availability of degree programs, and other personal factors.

As data on students' eventual economic outcomes become increasingly available, researchers can expand and improve on the measures developed here to provide deeper insights into the economic returns those investments achieve.

Introduction

It pays to get a college degree. Compared to typical individuals with only a high school diploma, typical bachelor's degree holders earn $580,000 more and associate's degree holders $245,000 more over their careers.[1]

Yet coming out of the Great Recession, college graduates found it difficult to find jobs on well-paying career paths, especially if their degrees were in something other than high-demand fields like STEM (science, technology, engineering, and math) or business.[2] Many are questioning the value of increasingly expensive college degrees and calling for greater transparency in connecting the college experience to economic reward.[3]

Individual outcomes for college students vary widely.[4] Personal characteristics matter, of course, and a great deal of variation across institutions in alumni success owes to the fact that so-called "selective" universities invest significant effort into admitting only the students they believe will be successful in school and after graduation. For their part, students often apply to and enter schools that align with their academic ability and future labor market prospects. Many students, however, are simply unprepared to do well in college.[5]

The characteristics of the college matter as well, and among the most important are the policies and systems a college has in place to ensure that its students graduate. Many students do not graduate. For example, only 61 percent of bachelor's degree-seeking students finish their degree within twice the normal time at the institution where they started their education; the rate is just 38 percent for those in two-year programs.[6] Policies such as reducing school costs and providing academic support seem to make an enormous difference in graduation rates.[7] More selective universities often implement these policies to a greater extent, and students with identical qualifications graduate at much higher rates when they attend more selective universities.[8] This is true for low-income students, who often benefit from the greater scholarship opportunities selective institutions tend to provide.[9]

Another important college characteristic may be selectivity itself, as several studies have found that attending more selective schools raises future earnings, even for those with the same ability.[10] Other evidence suggests the differences in selectivity must be large to affect earnings of white or middle-class students,[11] but there is strong evidence that black and Hispanic students benefit from higher earnings after attending a more selective college.[12] In one experimental study of job applications, employers valued candidates from more selective colleges more highly than they did candidates with degrees from online colleges, despite otherwise identical resumes.[13]

Aside from student support policies and rough measures of quality such as selectivity, schools also vary—and outcomes may vary as a result—in terms of the quality of their instructional staff and the curriculum or mix of majors. While almost any course of study may be available to students at large public universities, many smaller four-year colleges or community colleges specialize in distinct fields like the arts, health care, culinary studies, or STEM. Thus, students attending these schools, securing career-building majors and acquiring specific, valuable skills, ought to be better prepared for some careers over others, regardless of how their preferences evolve. The decision to pick one field of study over another has profound effects on lifetime earnings, even for students with similar scores on standardized exams.[14]

There is increasing interest in quantifying the various measures of college quality so that consumers and policy makers can evaluate institutions.[15] The Obama administration has taken steps to enhance consumer transparency by devising a college scorecard offering information on cost, graduation rates, and loan default rates. This information is helpful but provides a limited picture of the value that colleges deliver.

Likewise, popular private rating systems shed some light on aspects of college quality but have two major flaws: They are largely based on selectivity alone, and they are unavailable for the vast majority of schools.

Fortunately, new advances in technology and business models, as well as state-level policy reforms, are starting to increase transparency. Various human resources websites collect detailed economic information from millions of alumni, and states are starting to disclose administrative data that link alumni earnings to colleges. Websites such as PayScale and LinkedIn collect salary and skills information with institutional detail for millions of graduates. College Measures publishes data showing earnings for recent graduates of colleges in six states. All of these data, while imperfect, provide new opportunities to assess college quality with respect to graduates' economic outcomes for a much wider swath of institutions than conventional rankings cover.

This report builds on these advances to develop new ways of measuring the economic value that U.S. colleges provide. The next section defines the specific policies and practices that we believe constitute important aspects of college quality, and then proceeds to show that the newly available outcome measures used here have empirical validity (in that they actually predict student economic outcomes using government tax records); it then explains which factors determine economic success and which schools tend to perform best on various predictors of alumni success; the final sections describe which schools most exceed their peers on student outcomes, relative to predictions, and how value-added measures compare to popular rankings. Ultimately, these measures can help students make better choices, college and regional leaders assess where they stack up on important quality measures, public and private leaders and donors in higher education more effectively prioritize student success, and researchers improve their own methods for understanding how educational institutions affect individual and collective prosperity.

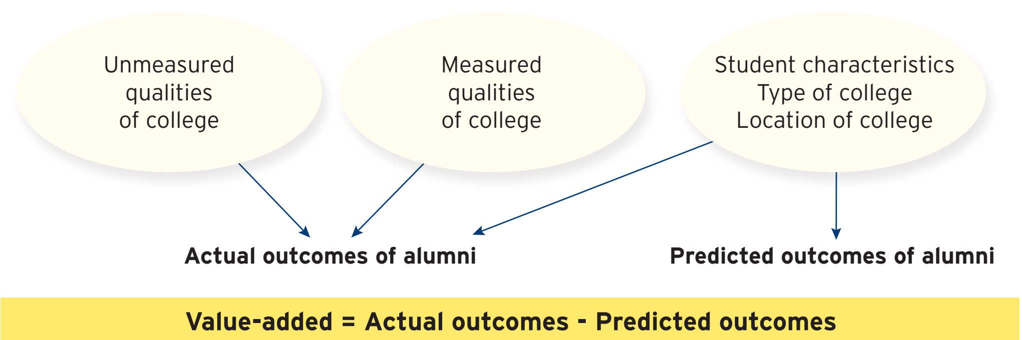
Methods

This section defines the metrics used to assess college quality, the method for constructing them, and the source of the underlying data. See the technical appendix for more detail and a discussion of the econometric models used in the analysis.

The theory underlying this analysis is that student economic outcomes, such as future salaries, are affected by student characteristics (such as their academic preparation, age, racial or ethnic background, and family income), the type of college (a community college or research university, for example), the location of the college (as in a big city with many jobs compared to a small town), and the qualities of the college (see Figure 1). To estimate the college's qualitative contribution to student outcomes, independent of its type, outcomes for an individual college are predicted based on institutions with similar profiles and locations.

Quality has measured and unmeasured components. The measured aspects of quality include how well the college pays teaching faculty, how much aid it gives to students (a measure of the economic value offered to students), how its curriculum and skills conferred align with high-paying careers, and whether the college has effective strategies for helping students remain at the college (retention rate) and complete their degree program (graduation rate). Some aspects of quality—such as the presence of a great president, development staff, or teaching faculty—cannot be measured, at least with existing data sources.

Figure 1. How Value-Added Is Calculated



Without knowing the quality of the college in the ways described above, the college's student, institutional, and locational characteristics can be used to predict student economic outcomes. The difference between this predicted outcome and the actual economic outcome is the college's value-added, compared to other institutions.[16]

For example, Springfield Technical Community College in Massachusetts and Bakersfield College in California share the same predicted student-loan repayment rate of 83 percent, which is roughly in the middle for community colleges. Predicted repayments are the same because the schools share a number of characteristics, and their differences balance out. They both primarily grant associate's degrees, and they are both located in areas with a cost of living slightly below the U.S. average. Bakersfield has a higher share of minority students, but students at Springfield Tech receive more federal Pell aid per student, suggesting greater economic disadvantage. But actual repayment rates are 85 percent at Springfield Tech versus 72 percent at Bakersfield. Thus, Springfield Tech has a higher value-added score on loan repayment of 13 percentage points.

Value-added is meant to capture the degree to which the college itself affects student economic success post-graduation. It represents the college's output, such as alumni earnings, less the characteristics of its students at the time of admission and the college's institutional type and location. The final value-added measure shows the extent to which the institution's alumni outcomes are above or below the average of its peer institutions with the same or similar student, type, and location characteristics. It does not assess the value of going to that college as compared to forgoing a postsecondary education or the return on investment per dollar spent.[17]

This is not the first attempt to measure value-added across colleges. Education economists have used value-added models in the context of predicting wage earnings in Texas, where detailed administrative data are available at the student level.[18] Others have estimated value-added with respect to graduation for four-year colleges using college-level metrics from the Department of Education.[19]

The next section describes the categories of indicators that make up the remainder of the analysis: graduate economic outcomes and associated value-added measures; student and institutional characteristics; and college quality factors that contribute to graduate economic success.

Graduate economic outcomes and associated value-added measures

This study calculates college value-added separately with respect to three basic economic outcome measures for each institution's graduates: alumni *mid-career salary* (available for 1,298 institutions), *federal student loan repayment rates* (available for 6,155 institutions), and *occupational earnings potential* (obtained for 2,433 institutions). Final rankings of schools on a 1–100 scale will separate two-year and four-year colleges, but one can compare the value-added measures between them.

Alumni mid-career salary: median total earnings by college for full-time workers with at least 10 years of experience. These data come from PayScale.com, which collects data directly from graduates who log onto the website and enter their information in exchange for a free "salary report." Mid-career earnings were chosen because they better approximate earnings over the course of one's working career and are easier to explain statistically. For the main measure reported here, earnings are limited to alumni with a bachelor's degree for colleges that primarily award bachelor's degrees or higher, and to alumni with an associate's degree for institutions that primarily award degrees of two years or fewer.[20] In this way, the earnings measure is not affected by the probability that alumni go on to earn higher-level degrees from other schools.[21] Data from this report available online will include a value-added measure using salary data from all graduates for the limited number of four-year colleges with available data. These data, analyzed in the appendix, are not available for community colleges.

Federal student loan default rates: the percentage of a college's attendees who default on their federal student loans within the first three years after repayment begins. To minimize variance due to annual fluctuations for small schools, the total number of defaults from 2009 and 2014 was divided by the total number of borrowers during 2009 to 2011, so that defaults were included only for the same cohort (such that defaults from those who borrowed in 2012 or later are not included in the numerator). Missing values were given to colleges with fewer than 10 borrowers or fewer than 30 borrowers if the number of borrowers comprised fewer than 5 percent of graduating students. These data come from the Department of Education.[22] This report converts default rates to repayment rates for ease of comparison with positive economic outcomes.

Occupational earnings power: the average salary of the college alumni's occupations. Alumni occupational data come from LinkedIn, and are used to weight earnings data (national wages by occupation) from the Bureau of Labor Statistics Occupational Employment Survey to arrive at an average salary figure.[23] For this measure, all alumni contribute to the final value, even if they have earned a higher degree from a different institution. This occupational earnings power measure expresses the average market value of the careers for which a college presumably prepared its graduates and is more broadly available than the alumni mid-career earnings measure derived from PayScale.

College value-added, with respect to alumni mid-career salary: the percentage increase or decrease in mid-career salary above or below what is predicted based on student and school characteristics. The comparison is the average institution, so that a negative score means alumni are earning below

Why consider only economic outcomes?

This study focuses on economic outcomes—mid-career earnings, occupational earnings, and student loan repayment rates—for several reasons. Earnings are a major and important measure of well-being; earnings data are relatively precise and easy to obtain; and income and other labor market outcomes have important civic and public policy implications, in terms of their effects on other people and tax revenues.

Of course, there is more to life than purchasing power, and the value-added method described here can be applied to any measurable outcome. For example, PayScale provides survey data by major and college on the percentage of graduates who believe their job makes the world a better place. The percentage of a college's students who complete degrees in fields such as theology, health care, education, and biology is closely associated with that value measure. But whether concepts like meaning, happiness, and living a good life can be validly measured is beyond the scope of this paper.

the average institution with similar student and institutional characteristics. A negative score does not imply that the college's alumni would have been better off not attending.

College value-added, with respect to federal student loan repayment: the percentage-point increase or decrease in federal student loan repayment rates above or below what is predicted based on student and school characteristics. This value-added metric is estimated twice: once with the full-specified model and again with a more parsimonious model that excludes LinkedIn data and teacher salaries. The latter allows for the calculation of value-added for a much larger number of colleges but is less precise.

College value-added, with respect to occupational earnings power: the percentage increase or decrease in the average salary of the occupations in which alumni work above or below what is predicted based on student and school characteristics.

Student characteristics

The variables used to control for the characteristics of students at the time of admission and the type of institution they attend are derived mostly from the Department of Education's Integrated Postsecondary Education Data System (IPEDS), which requires colleges eligible for federal postsecondary financial programs to report detailed data (see Table 1 for full list). These variables include:

- ***Student enrollment data on race, gender, age, out-of-state status, and part-time enrollment share:*** For individuals, race, gender, and age are strong predictors of earnings, even controlling for education, so these variables should collectively also predict alumni-level earnings or other economic outcomes. Foreign-born or out-of-state students exhibit greater discretion than students who enroll in their local university and are likely to be more academically prepared.[24] Part-time students are more likely to be economically and academically disadvantaged.[25]
- ***Percent receiving no aid or receiving federal loans, and Pell grant aid per student:*** Colleges submit financial aid data to IPEDS, and these data provide indirect information on student family incomes, which in turn predict preparation for academic success. Pell grant aid, for example, is strictly needs-based and decreases as family income increases. Therefore, the average student's Pell grant aid provides an indication of student financial need (and, for that reason, is a slightly better predictor of student outcomes than the percentage receiving Pell grants of any size).[26] If students are receiving no aid, it is less likely they are from low-income families.

Table 1. Control Variables Used to Predict Alumni Outcomes

Student characteristics	Type of college	Location of college
Enrollment	Modal degree is one year	Local price index 2012
Percent of freshman from same state	Modal degree is bachelor's	State location
Foreign-born student share of enrollment	Modal degree is post-bachelor's	
Asian student share of enrollment	Online college (all students enrolled only in distance learning)	
White student share of enrollment	Carnegie classification	
Average age of students	Percentage distribution of degrees granted by level	
Percent attending part time		
Female share of students		
Percent of students receiving no aid		
Percent of students receiving federal loans		
Pell grant aid per student		
Imputed standardized math scores		
LinkedIn salary bias		

- **_Student test scores:_** Specifically, these are results from admitted students on the quantitative sections of the SAT and ACT (those sections are most predictive of student outcomes after graduation). Test scores on both exams were first standardized to have mean zero and a standard deviation of one. Then a weighted average was calculated using the percentage of admitted students who took each exam. For the large number of colleges with no admissions requirements or reported test score data, imputed test scores are used instead. The model used to predict student test scores is described in the appendix and based largely on student demographics and financial information.
- **_LinkedIn salary bias:_** Since two of the outcomes (mid-career salary and occupational earnings power) are measured using LinkedIn and PayScale, it is important to adjust for potential bias in the use of these social media websites.[27] A college-specific measure of the LinkedIn bias is calculated based on how well the fields of study of LinkedIn users match actual graduates. The PayScale bias could not be calculated directly. The extent of the PayScale bias will be discussed below, and both sources are described in the appendix.

Institutional characteristics

The variables used to control for the type of institution students attend include:

- **_Carnegie Classification of Institutions of Higher Education:_** This framework distinguishes colleges by mission, administrative details, and degree-award levels. It is frequently used as a way to classify different institutions into similar categories for research purposes.
- **_Local price index:_** Drawn from the Bureau of Economic Analysis, this index captures the local cost of living, for which housing costs are the most important element. Since salaries for even nonspecialized jobs are higher in expensive cities like New York, this is an important adjustment, since many graduates reside in or around the region of their college.
- **_State location:_** Because labor markets vary by state, this is also an important adjustment.

College quality factors

The analysis considers college "quality" factors as distinct from student and institutional characteristics. A variable was considered a potential quality factor if it met the following criteria: (1) it affects alumni economic performance, or is at least significantly correlated with it; (2) it is not a direct measure of economic success (like employment in a high-paying career); and (3) it is something colleges can influence, at least partially, regardless of their institutional focus (medical schools vs. culinary schools) and location. These criteria limited the list of quality factors to seven concepts:

Curriculum value: the labor market value of the college's mix of majors. This is calculated by determining the national median earnings for all bachelor's degree holders in the labor force by major, using the Census Bureau's 2013 American Community Survey (ACS), made available by the Integrated Public Use Microdata Series (IPUMS).[28] A weighted average for each school is then calculated using the actual number of graduates in each major, with data from IPEDS. Nongraduates are not included in the analysis because enrollment data are not available by detailed major and students may switch majors before completion.[29]

Share of graduates prepared to work in STEM fields: the percentage of graduates who complete a degree in a field of study that prepares them for an occupation demanding high levels of science, technology, engineering, or math knowledge. The number of graduates by field comes from IPEDS data, and the STEM-relevant knowledge requirements of occupations are based on an analysis of O*NET data, as described in the appendix. This method classifies a diverse group of majors as STEM, including health care, business, design, blue-collar trades, and education. The calculation includes all students completing awards at the institution.

Value of alumni skills: the labor market value of the 25 most common skills listed on the LinkedIn resumes of alumni who attended the college. These skills were matched with data, compiled by the labor market intelligence firm Burning Glass, on skills and salaries advertised in millions of job vacancies. The skills listed on LinkedIn were not necessarily acquired at the college.

Graduation rate, twice normal length: the percentage of enrolled students who graduate from the college in eight years for four-year programs and four years for two-year programs.

Table 2. Summary Statistics for Enrollment, Value-Added, Outcomes, and Various Quality Metrics Used in Analysis for All Colleges and by Two- and Four-Year Schools

	Enrollment 2012-2013	Value-added, salary	Value-added, repayment rate on loans	Value-added, occupational earnings power	Value-added, repayment rate on loans (broad measure)	Mid-career earnings	Loan repayment rate, 2009-2011 borrowers
	Mean						
All colleges	3,879	7%	0.0	1%	0.0	$70,613	85.1
Primarily 2-year	2,760	-2%	-2.4	-1%	-0.3	$54,252	81.6
Primarily 4-year or higher	6,103	9%	1.6	2%	0.4	$75,916	91.3
	Observations						
All colleges	7,394	1,139	1,785	1,867	4,400	1,298	6,155
Primarily 2-year	4,892	275	704	782	2,738	318	3,902
Primarily 4-year or higher	2,485	864	1,081	1,085	1,662	979	2,241

Retention rate: the share of students from the full-time and part-time adjusted fall 2012 cohorts still enrolled in fall 2013.

Institutional aid per student: financial aid funded by the college itself, rather than federal or other sources.

Average salary of instructional staff: the average compensation of all instructional staff at the college.

Other variables were considered as potential quality or control measures but rejected because they did not improve the predictive power of the model, given the other variables. These include: student-to-faculty ratio, average net cost of tuition, transfer rates, percent of students using distance learning, for-profit status of college, and the percentage of teachers with adjunct status.

A summary of the main variables is provided in Table 2, with the mean overall and by type of college, as well as the number of observations available. Value-added metrics are calculated for as few as 1,139 colleges with respect to mid-career earnings and as many as 4,400 colleges using the broadest available measure of value-added with respect to loan repayment. Quality measures such as the curriculum value, the STEM share of graduates, and institutional aid are available for almost all 7,400 colleges.

Findings

Data from private social media sources can empower consumers of education.

Since neither colleges nor all but a few state governments provide information on the post-attendance economic outcomes of college students, assessments based on such information must turn to privately available sources. PayScale appears to be the most promising. In exchange for a free "salary report"—showing how a user's earnings stack up against peers in his or her field—anyone can create an account on PayScale after entering information on where they attended school, what they studied, and how much they earn.

There are a number of ways one can assess whether or not PayScale accurately captures the earnings of graduates—or whether the sample is statistically biased by the voluntary nature of its data collection.

Broadly, PayScale earnings by major for U.S. residents with bachelor's degrees can be compared to similar data from the ACS, which annually samples 1 percent of the U.S. population.[30] The correlation between the two is what matters most for this analysis, since value-added calculations are based on relative differences between predicted and actual earnings.

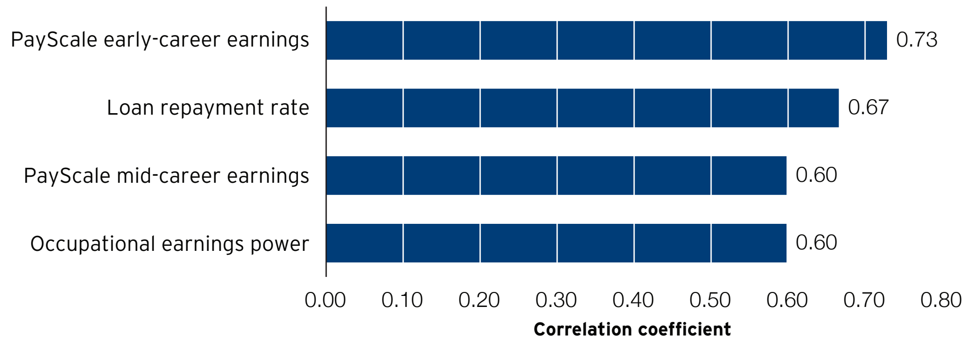
Occupational earnings power	Curriculum value	Value of alumni skills	Graduates in STEM fields, pct.	Average institutional financial aid	Graduation rate, within twice normal time	Retention rate	Average faculty salary	Pell aid per student
$62,254	$50,883	$63,104	23%	$2,327	55	67	$71,212	$2,028
$60,572	$49,230	$59,664	21%	$723	57	65	$62,246	$2,195
$63,874	$54,291	$65,812	26%	$5,648	51	71	$79,480	$1,654
2,433	7,343	2,162	7,383	7,394	5,822	5,666	4,396	7,041
1,193	4,881	950	4,892	4,892	3,913	3,733	2,068	4,863
1,239	2,457	1,211	2,485	2,485	1,900	1,922	2,322	2,164

The correlation between bachelor's degree holders on PayScale and median salaries by major for workers in the labor force from the Census Bureau is 0.85 across 158 majors matched between the two databases. Averaged across majors, the ACS median salary falls between the median early and mid-career salaries listed on PayScale. Specifically, the ACS median is $12,000 above the PayScale early career salary and $18,000 below the PayScale mid-career salary. The salaries of associate's degree earners on PayScale by major are also highly correlated with the ACS data (0.76), despite the fact that the ACS collects earnings by field of study only for those earning a bachelor's degree.[31]

At the college level, alumni mid-career earnings and other economic outcomes for graduates can be compared to other publicly available data in a limited number of cases. Some states report earnings data from unemployment insurance records, which are generated for almost every worker and are legally required to be accurate and timely. Among the small number of states that collect and publicly share this information for public colleges, the Texas Higher Education Coordinating Board (THECB) provides these data on its website in a format that is conducive to statistical analysis. THECB lists median earnings by institution and major for the fourth quarter of the year following student graduation. These records are limited in that they provide no information about how many hours the students are working and what their annual salary would be if they worked full time. Moreover, since these data reflect students' first jobs after graduation, they are likely to greatly understate lifetime earnings potential, especially if the graduate plans on attending graduate school before starting his or her career. Nonetheless, the data are instructive.

The three economic outcome measures (alumni mid-career salary, federal student loan repayment rates, and occupational earnings power) all correlate highly with earnings immediately after graduation for Texas colleges (see Figure 2).[32] Early-career earnings from PayScale explain the early-career Texas earnings better than PayScale's mid-career earnings measure, as expected (with 0.73 vs. 0.60 correlation coefficients, respectively), since the Texas data contain income only just after graduation. Student loan repayment rates within the first three years of graduation (0.67) and occupational earnings power (0.56) also correlate well with income soon after graduation. Importantly, these strong correlations show that data from PayScale and LinkedIn, and data on student loan repayment rates, capture important aspects of graduate economic success.

Figure 2. Correlation Coefficient of Median Wages of Recent Texas Graduates With Outcome Measures Used in This Report



Source: Authors' analysis of data from Texas Higher Education Coordinating Board, U.S. Department of Education, PayScale, and LinkedIn.

A college's curriculum value, the skills its alumni possess, and its completion rates strongly predict economic outcomes for its graduates.

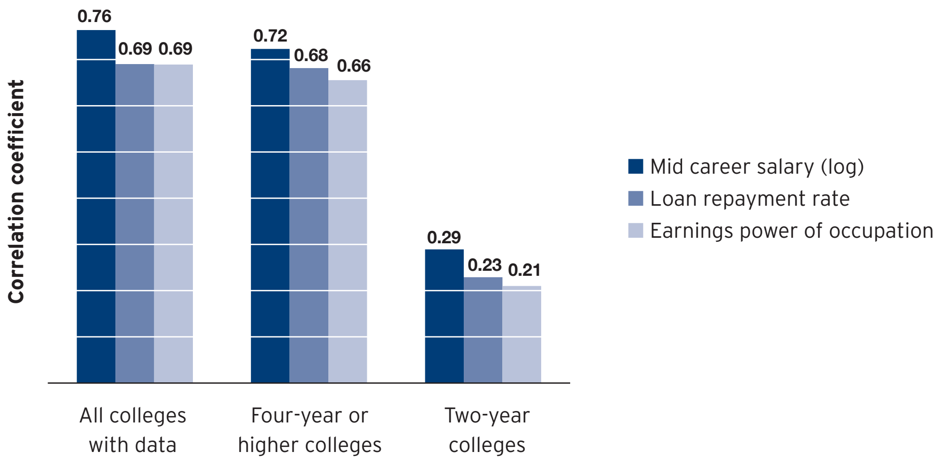
Most economics research models predict workers' earnings as a function of their gender, years of experience, and human capital as measured by years of education.[33] The PayScale mid-career earnings for bachelor's degree holders by institution hold workers' experience and years of education constant, and yet differences across institutions remain large. This section examines some of the factors that may explain these differences in economic outcomes across colleges.

Student characteristics: Among college attendees, student characteristics differ widely and clearly affect earnings after graduation. For example, students with higher cognitive scores—measured in a variety of ways, including college entrance exams—tend to earn higher salaries.[34] Likewise, students from lower-income families exhibit lower earnings. The race, age, and gender of students affect their later earnings as well.

For each of the three post-attendance outcomes measured here—mid-career salary, loan repayment rate, and occupational earnings power—student test scores, math scores in particular, are highly correlated: 0.76 for mid-career salaries and 0.69 for student loan repayment and occupational earnings power (Figure 3). Other student characteristics, such as the percentage receiving Pell grants, also correlate highly with these outcomes, though not as highly as test scores. In all cases, however, the relationship between these measures and test scores is much closer for four-year colleges than for two-year colleges. The lower correlation is partly expected, since test scores are imputed for two-year colleges and thus less precisely measured.

In addition to test scores, other demographic differences distinguish the 10 colleges with the highest- and lowest-earning alumni. The top-earning schools—such as Cal Tech, MIT, Harvey Mudd, Washington University in St. Louis, the University of Chicago, Harvard, and Princeton—have very low percentages of students receiving needs-based financial aid under the Pell grant program and fewer black and Hispanic students than do lower-scoring schools. To illustrate, just 19 percent of students receive Pell grants at colleges in the top decile of test scores (95 colleges), compared to 53 percent of students in the bottom decile (87 colleges). Just 13 percent of students are black or Hispanic in the top decile-scoring colleges, compared to 49 percent at colleges in the bottom decile. Likewise, women are overrepresented at colleges in the bottom of test scores compared to the top (63 percent vs. 49 percent).

Figure 3. Correlation Between Student Test Scores and Economic Outcomes



Source: Authors' analysis of data from U.S. Department of Education, PayScale, and LinkedIn.

Institutional characteristics: Aside from student test scores, colleges have different missions and specializations. Some focus entirely on training lawyers or doctors, while others specialize in cosmetology or religious vocations. Of course, schools also differ widely in the level of education they offer. The Carnegie classification organizes the diverse array of postsecondary institutions into similar categories, based on characteristics like degree award levels given, research orientation, and private or public status.[35]

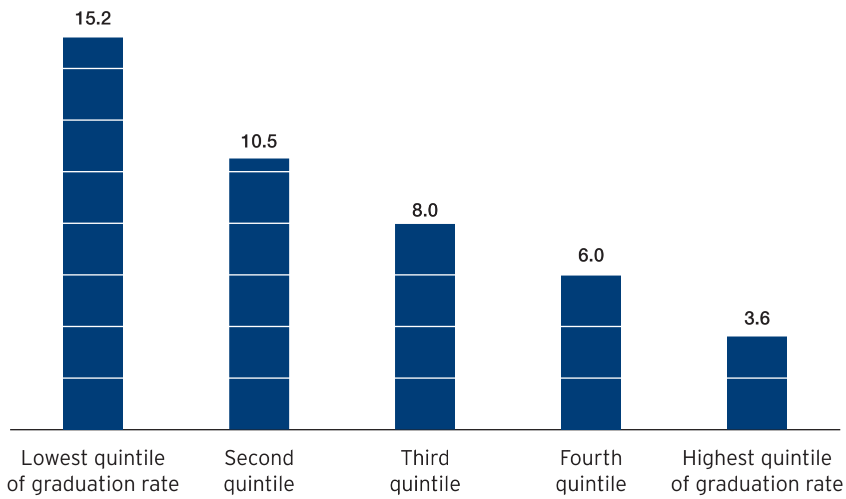
With $103,000 in average earnings, graduates from schools of engineering earn more than any other Carnegie institutional type, according to PayScale data. Research universities with very high research activity are next, with average earnings of $89,000, followed by liberal arts and sciences colleges ($83,000). Graduates from these schools also tend to have low default rates on student loans and work in high-paying occupations. Graduates from associate's degree-granting colleges generally earn lower salaries.

Graduation rates: Since workers with a college degree earn more and are employed at higher rates than those without a degree, a school's graduation rate should relate closely to attendees' economic outcomes.

Across all postsecondary institutions, college graduation rates are highly correlated with the three outcome variables considered in this report (0.82 for repayment rates, 0.75 for mid-career earnings, and 0.52 for occupational earnings power). This suggests that a higher probability of degree completion is not the only benefit derived from attending a school with a high graduation rate.

Indeed, among schools granting a bachelor's degree or higher, default rates for federal student loans average 15.2 percent for schools in the bottom quintile of graduation rates but just 3.6 percent for institutions in the top quintile (Figure 4). For primarily two-year colleges, the gap is not as large: 19.4 percent default rates for the bottom quintile by graduation rate compared to 16.3 percent for the top quintile. It is worth noting, however, that students in associate's degree programs are less likely to take on student debt than those in four-year programs.[36]

Figure 4. Average Default Rates on Student Loans Within First Three Years, by Quintile of Graduation Rate, for Primarily Four-Year or Higher Degree-Granting Institutions



Source: Authors' analysis of U.S. Department of Education data

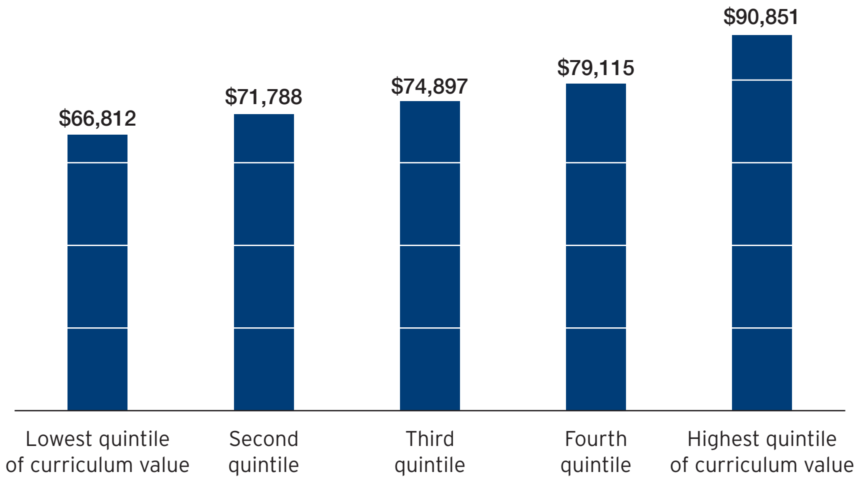
Curriculum value and value of alumni skills: A school's mix of course offerings and majors—its curriculum—also shapes the potential earnings of its graduates. For example, degree holders in STEM fields typically earn more than their counterparts in others majors.[37] Even within a given major, course offerings and specialized skills offered by specific schools can make a large difference in earnings. For example, job vacancy advertisements reveal that certain computer science skills (e.g., Ruby on Rails, Android, iOS) are far more valuable than others (e.g., PERL or more general skills like data mining and helpdesk support).[38] Hence, both the mix of completions by field of study and the actual skills acquired by those who attend a college affect economic outcomes.

Graduates from four-year colleges in the top quintile by curriculum value earn $91,000 a year on average, $24,000 more than those in the bottom quintile (Figure 5). Schools with the highest curriculum value include the Colorado School of Mines, the Rose-Hulman Institute of Technology, the Missouri University of Science and Technology, the Polytechnic Institute of New York University, the Worcester Polytechnic Institute, the Stevens Institute of Technology, and Rensselaer Polytechnic Institute. Better-known science and engineering colleges like Cal Tech, Georgia Tech, MIT, and Carnegie Mellon also rank near the top.

There is considerable overlap between curriculum value and the value of alumni skills. Yet curriculum value, in itself, contains no information on the quality of the same curriculum offered at one school versus another. The value of alumni skills, however, represents the market value of specific qualifications that alumni list on their resumes, which likely vary across institutions even within the same field of study.

Alumni from Cal Tech list the highest-value skills on their LinkedIn profiles (Table 3); their skills include algorithm development, machine learning, Python, C++, and startups (that is, starting a new business). Cal Tech is followed closely by Harvey Mudd and MIT. Babson College, also in the top 10, focuses on business rather than science; its course offerings teach many quantitative skills relevant for business-oriented STEM careers. Many graduates from the Air Force Academy are prepared for high-paying engineering jobs in the military and at large defense contractors. They list skills like aerospace and project planning. By contrast, the skills of graduates from art and design schools or criminal justice colleges generally garner lower salaries, at least when advertised by employers.

Figure 5. Mid-Career Earnings by Quintile of Curriculum Value, for Primarily Four-Year or Higher Degree-Granting Institutions



Source: Authors' analysis of data from PayScale, the Census Bureau's 2013 American Community Survey (via IPUMS), and Department of Education

Turning to two-year colleges, the skills listed by alumni tend to command lower salaries than do the skills listed by their counterparts from bachelor's or higher institutions. Yet, certain community or two-year colleges stand out as graduating alumni with relatively high-value skills. At the top of the list is the SUNY College of Technology at Alfred, also known as Alfred State. Many of its alumni are skilled at the engineering software AutoCad, management, and Microsoft software applications. Alumni of Triton College, in the Chicago area, are well versed in professional business software and management skills. For the New England Institute of Technology, skills like troubleshooting, VMware, and servers boost the earnings of its alumni.

Graduates of colleges with high value-added enjoy much more economic success than their characteristics at time of admission would suggest.

In best-practice teacher evaluations at the K-12 level, teachers are not rated lower or higher based entirely on their students' test scores. Administrators recognize that students from less-advantaged households are unlikely to consistently score higher than students from privileged households, even within the same classroom. An analogous idea in higher education is that colleges should not be credited (or punished) for recruiting students whose skills were nourished (or neglected) over the course of 18 years by parents and previous educators. What matters more is the value that schools contribute to success. This is the approach used here.

The first step is to see how measurable aspects of quality relate to alumni outcomes for students with similar characteristics at similar types of colleges. The analysis starts with earnings, then occupational earnings power, and then repayment rates.

Alumni mid-career earnings: Of the seven quality metrics—curriculum value, percent graduating in a STEM field, alumni skills, graduation rate, retention rate, aid per student, and instructional staff salaries—the first five predict significantly higher mid-career salaries across colleges. Curriculum value is the most powerful predictor (Figure 6). Graduates from a college with curriculum values at least one standard deviation above the mean earn 6.9 percent higher salaries than other graduates, holding other factors constant. The STEM share of graduates and the average value of alumni skills add 3.5 and 3.0 percent to earnings, respectively. Higher graduation and institutional aid also predict higher earnings.

Table 3. Colleges Whose Alumni Have the Most Valuable Skills Listed on LinkedIn, by Type of College

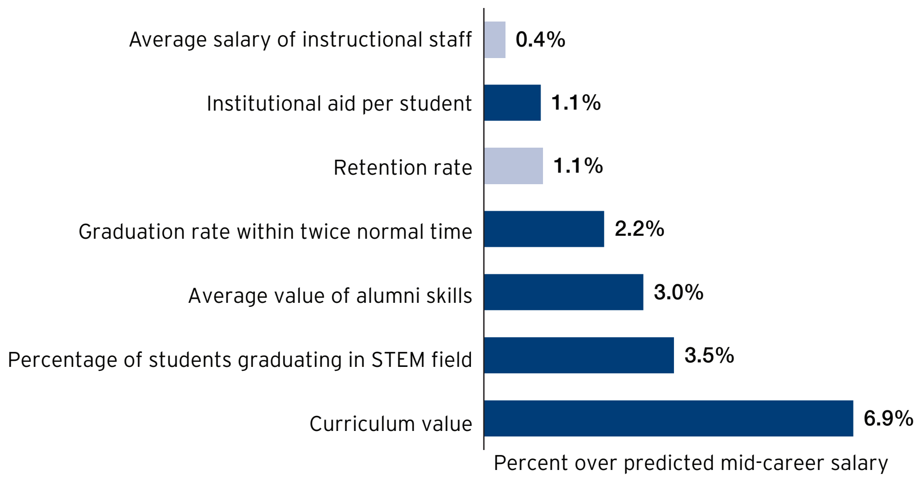
	Value of alumni skills	Curriculum value	Median mid-career salary	Metropolitan area
Four-year or more colleges whose alumni possess most valuable skills				
California Institute of Technology	$91,029	$78,593	$126,200	Los Angeles-Long Beach-Anaheim, CA
Harvey Mudd College	$90,574	$75,698	$133,800	Los Angeles-Long Beach-Anaheim, CA
Massachusetts Institute of Technology	$88,046	$73,541	$128,800	Boston-Cambridge-Newton, MA-NH
Polytechnic Institute of New York University	$86,497	$78,757	$110,400	New York-Newark-Jersey City, NY-NJ-PA
United States Air Force Academy	$85,495	$68,678	$118,400	Colorado Springs, CO
Carnegie Mellon University	$84,543	$68,717	$111,700	Pittsburgh, PA
Babson College	$83,946	$60,105	$117,400	Boston-Cambridge-Newton, MA-NH
Embry-Riddle Aeronautical University-Daytona Beach	$83,749	$74,240	$83,000	Deltona-Daytona Beach-Ormond Beach, FL
Rensselaer Polytechnic Institute	$83,140	$75,665	$110,100	Albany-Schenectady-Troy, NY
United States Military Academy	$83,048	$66,921	$123,900	New York-Newark-Jersey City, NY-NJ-PA
Two-year or lower colleges whose alumni possess most valuable skills				
SUNY College of Technology at Alfred	$69,219	$55,208	$53,500	Alfred, NY
Triton College	$66,747	$51,428	$59,200	Chicago-Naperville-Elgin, IL-IN-WI
Harper College	$65,920	$53,468	$61,400	Chicago-Naperville-Elgin, IL-IN-WI
NHTI-Concord's Community College	$65,617	$58,339	$68,700	Concord, NH
St. Petersburg College	$65,499	$51,288	$54,000	Tampa-St. Petersburg-Clearwater, FL
Florida State College at Jacksonville	$65,435	$52,600	$50,800	Jacksonville, FL
Erie Community College	$65,248	$53,823	$52,800	Buffalo-Cheektowaga-Niagara Falls, NY
SUNY College of Technology at Delhi	$65,057	$53,560	$47,500	Delhi, NY
New England Institute of Technology	$65,023	$52,173	$58,500	Providence-Warwick, RI-MA
Broward College	$65,007	$50,918	$54,300	Miami-Fort Lauderdale-West Palm Beach, FL
Average for all four-year or higher colleges	$66,056	$56,071	$76,423	
Average of all two-year or lower colleges	$61,048	$52,945	$54,285	

Source: Authors' analysis of data from LinkedIn, Burning Glass, PayScale, the Census Bureau's 2013 American Community Survey (via IPUMS), and Department of Education. Averages are for colleges with non-missing data for each field.

Colleges that emphasize a strong STEM education are among the top performers on value-added with respect to earnings. These include highly selective schools such as Cal Tech, which has the highest value-added with respect to salary, MIT, Rose-Hulman, Stanford, Harvey Mudd, and Rice (Table 4). Graduates from Rose-Hulman in Terre Haute, Ind. work in leading advanced industrial companies like Eli Lilly, Rolls Royce, and Caterpillar. Graduates from NYU Polytechnic Institute often work for IBM, Wall Street companies, and AT&T. For these colleges, at least half of value-added comes from the sum of curriculum value, alumni skills, and STEM orientation.

The high value-added four-year colleges and universities, however, are not all STEM-focused. Unmeasured factors explain about half of value-added for liberal arts colleges on the list of top performers—St. Mary's University, Marietta College, Colgate University, SUNY Maritime College, Carleton College, Bradley University, Manhattan College, and Washington and Lee University. These unmeasured characteristics amount to an "x factor." They may consist of things like administration or teaching quality, student ambition, or alumni networks. Whatever the reason, Colgate, Carleton, and Manhattan place many graduates into top international companies like IBM, Google, JP Morgan, and Wells Fargo. Marietta alumni often work in the energy sector for firms like Chevron and BP.

Figure 6. Percent Increase in Mid-Career Salary (Above Predicted) for One Standard Deviation Increase in Quality Variable, 1139 Postsecondary Institutions



Note: Light blue bar indicates that effect is not statistically different than zero at 95% confidence levels.
Source: Authors' analysis of various sources

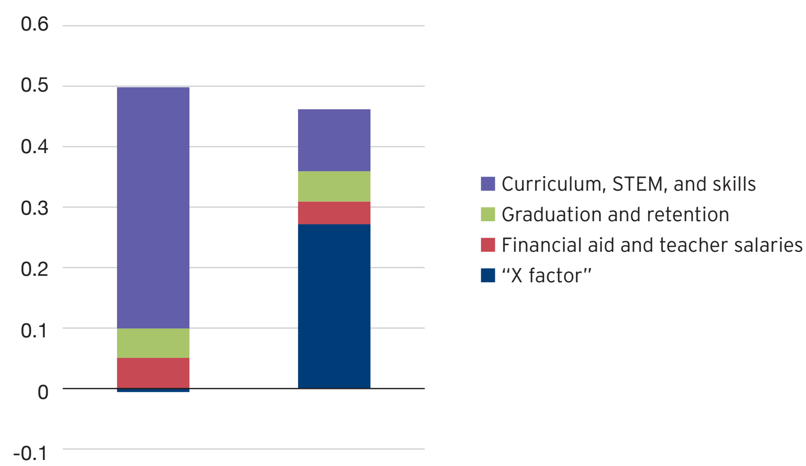
Table 4. Four-Year or Higher Colleges With the Highest Value-Added With Respect to Mid-Career Earnings

	Value-added	Predicted	Actual	Metropolitan area
California Institute of Technology	49%	$77,129	$126,200	Los Angeles-Long Beach-Anaheim, CA
Colgate University	46%	$79,774	$126,600	Syracuse, NY
Massachusetts Institute of Technology	45%	$82,439	$128,800	Boston-Cambridge-Newton, MA-NH
Rose-Hulman Institute of Technology	44%	$73,628	$114,100	Terre Haute, IN
Carleton College	43%	$76,236	$117,700	Faribault-Northfield, MN
Washington and Lee University	42%	$81,281	$124,300	Lexington, VA
SUNY Maritime College	42%	$79,637	$121,700	New York-Newark-Jersey City, NY-NJ-PA
Clarkson University	42%	$72,583	$110,700	Ogdensburg-Massena, NY
Manhattan College	42%	$72,701	$110,800	New York-Newark-Jersey City, NY-NJ-PA
Stanford University	41%	$83,864	$126,400	San Jose-Sunnyvale-Santa Clara, CA
Harvey Mudd College	40%	$89,466	$133,800	Los Angeles-Long Beach-Anaheim, CA
Rice University	40%	$80,379	$119,900	Houston-The Woodlands-Sugar Land, TX
Marietta College	39%	$62,795	$93,100	Marietta, OH
Virginia Military Institute	38%	$78,444	$115,000	Lexington, VA
Polytechnic Institute of New York University	37%	$76,245	$110,400	New York-Newark-Jersey City, NY-NJ-PA
Worcester Polytechnic Institute	37%	$76,688	$110,500	Worcester, MA-CT
St Mary's University	36%	$64,500	$92,500	San Antonio-New Braunfels, TX
Stevens Institute of Technology	36%	$82,827	$118,700	New York-Newark-Jersey City, NY-NJ-PA
Bradley University	35%	$67,307	$95,500	Peoria, IL
Georgia Institute of Technology-Main Campus	34%	$79,195	$111,700	Atlanta-Sandy Springs-Roswell, GA
Average of all four-year and higher colleges	9%	$68,790	$75,900	

Value-added in this calculation is the difference between actual and predicted earnings in log values. A zero value-added measure means the school's students earn the average for students like them at similar types of colleges.
Source: Authors' analysis of various sources

Thus, for any given college, value-added can be broken down into various observable and unobservable aspects of quality. The contributions to value-added are very different for the top two colleges—Cal Tech and Colgate (Figure 7). All of Cal Tech's value added is "observable," in the sense that it can be attributed to things like the value of skills taught and acquired, the mix of majors, and the STEM orientation; those three factors account for 81 percent of Cal Tech's value-added. But for Colgate, those factors explain just 22 percent of value-added, while 59 percent comes from unobserved x-factors.

Figure 7. Breaking Down Value-Added With Respect to Alumni Salaries for the Two Highest-Scoring Four-Year Colleges



Source: Authors' analysis of various sources

For two-year colleges, both actual and predicted salaries tend to be lower, as does the value-added contribution with respect to salaries (Table 5). The most outstanding colleges on this measure include NHTI-Concord's Community College, Lee College, Pearl River Community College, Pueblo Community College, Briarcliffe College, and Bakersfield College. (An important limitation here is that PayScale reports salary data for only a small fraction of the nation's postsecondary institutions offering degrees of two years or fewer.)

NHTI (New Hampshire Technical Institute), near Boston, scores at the top on value-added for two-year colleges. Its alumni post high-value skills on their resumes, enjoy a high-value curriculum, and land jobs at the region's hospitals, banks, and tech companies. Just outside Houston, Lee College's high-skilled graduates often work in the oil industry or as technicians in various advanced industries prominent in the region. For these colleges and Texas State Technical College in Waco and Northcentral Technical College in Wisconsin, a strong curriculum explains much of the high value-added performance.

At Pearl River, Pueblo, Bakersfield, and other schools, unmeasured "x factors" account for a much larger share of the school's value-added. At Pearl River, alumni find work in the Mississippi region's energy, health care, and defense sectors. Bakersfield graduates also benefit from proximity to the energy sector, working for companies like Chevron and Aera Energy, as well as to local school districts. San Diego City College graduates go on to work for organizations like the Navy, the school district, and even advanced industrial companies like Qualcomm and Scripps Health.

Table 5. Two-Year or Lower Colleges With the Highest Value-Added With Respect to Mid-Career Earnings

	Value-added	Predicted	Actual	Metropolitan area
NHTI-Concord's Community College	22%	$55,304	$68,700	Concord, NH
Lee College	21%	$55,971	$69,000	Houston-The Woodlands-Sugar Land, TX
Pearl River Community College	21%	$50,371	$62,000	Picayune, MS
Pueblo Community College	19%	$50,473	$61,100	Pueblo, CO
Briarcliffe College	19%	$51,201	$61,900	New York-Newark-Jersey City, NY-NJ-PA
Bakersfield College	17%	$56,957	$67,200	Bakersfield, CA
Texas State Technical College-Waco	16%	$55,257	$65,000	Waco, TX
San Diego City College	16%	$60,297	$70,900	San Diego-Carlsbad, CA
Heald College-Concord	15%	$55,653	$64,600	San Francisco-Oakland-Hayward, CA
Northcentral Technical College	14%	$50,302	$57,800	Wausau, WI
Minnesota State Community and Technical College	13%	$52,372	$59,900	Fergus Falls, MN
The Community College of Baltimore County	13%	$54,688	$62,300	Baltimore-Columbia-Towson, MD
Renton Technical College	13%	$56,294	$64,000	Seattle-Tacoma-Bellevue, WA
Navarro College	12%	$53,184	$60,100	Corsicana, TX
San Jacinto Community College	12%	$56,303	$63,200	Houston-The Woodlands-Sugar Land, TX
Massachusetts Bay Community College	11%	$55,895	$62,600	Boston-Cambridge-Newton, MA-NH
Corning Community College	11%	$55,054	$61,600	Corning, NY
Allegany College of Maryland	11%	$52,138	$58,300	Cumberland, MD-WV
Community College of Rhode Island	11%	$54,346	$60,700	Providence-Warwick, RI-MA
Lorain County Community College	11%	$52,614	$58,700	Cleveland-Elyria, OH
Average of all two-year or lower colleges	-2%	$55,040	$54,250	

Value-added in this calculation is the difference between actual and predicted earnings in log values. A zero value-added measure means the school's students earn the average for students like them at similar types of colleges.
Source: Authors' analysis of various sources

Occupational earnings power of alumni: Another way to assess a college's value-added is to examine the kinds of occupations that its graduates enter and the average pay for those occupations. These data (from LinkedIn) are more widely available than those for mid-career salary (from PayScale).

On this score, alumni skills, the share of graduates majoring in STEM fields, and curriculum value strongly predict a college's value-added with respect to occupational earnings power. Graduates from colleges with higher-paid teachers also tend to enter higher-paying careers (Figure 8). For this measure, graduation and retention rates add no additional predictive power, given skills, STEM orientation, and these other factors. Student aid actually predicts entry into lower-paying occupations.

Among four-year colleges, Worcester Polytechnic, the Colorado School of Mines, and the Charles R. Drew University of Medicine and Science generate the highest value-added with respect to occupational earnings power (Table 6). The latter is a historically black college with a strong health science curriculum. A high percentage of its graduates work in health care professions, according to LinkedIn data. Other top performers include Cal Tech, Lawrence Technological University, Harvey Mudd, the Wentworth Institute of Technology, the Milwaukee School of Engineering, and the Missouri University of Science and Technology.

Among primarily two-year colleges, Louisiana's Northshore Technical Community Colleges lands graduates into high-paying careers in operations, engineering, and health care. Concorde Career Colleges in Memphis, Tenn. and Portland, Ore. also seem to prepare students for well-paying careers in health care and operations. The unmeasured x-factors channel most of the value-added for top community colleges, but Vermont Technical College and Spartan College of Aeronautics and Technology in Tulsa, Okla. score well on STEM and skill orientations, boosting value-added.

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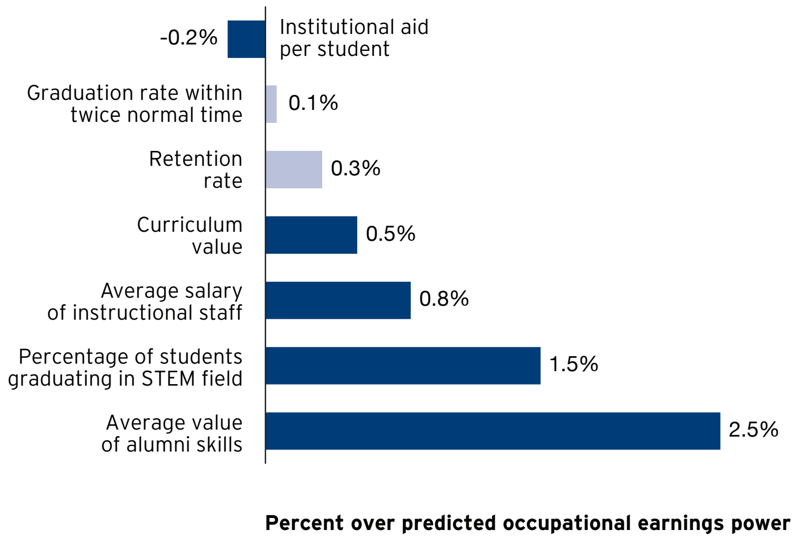
Table 6. Colleges With the Highest Value-Added With Respect to Occupational Earnings Power, by Type of College

	Value-added	Predicted occupational earnings power	Actual occupational earnings power	Metropolitan area
Four-year colleges with highest value-added with respect to occupational earnings power				
Worcester Polytechnic Institute	19%	$63,925	$77,593	Worcester, MA-CT
Colorado School of Mines	19%	$64,633	$78,155	Denver-Aurora-Lakewood, CO
Charles R Drew University of Medicine and Science	19%	$59,622	$72,025	Los Angeles-Long Beach-Anaheim, CA
California Institute of Technology	18%	$64,550	$77,458	Los Angeles-Long Beach-Anaheim, CA
Lawrence Technological University	18%	$62,762	$75,074	Detroit-Warren-Dearborn, MI
Harvey Mudd College	18%	$66,339	$79,179	Los Angeles-Long Beach-Anaheim, CA
Wentworth Institute of Technology	18%	$62,713	$74,733	Boston-Cambridge-Newton, MA-NH
Milwaukee School of Engineering	18%	$63,809	$76,015	Milwaukee-Waukesha-West Allis, WI
Missouri University of Science and Technology	17%	$65,076	$77,497	Rolla, MO
New Jersey Institute of Technology	17%	$64,384	$76,051	New York-Newark-Jersey City, NY-NJ-PA
Two-year or lower colleges with highest value-added with respect to occupational earnings power				
Northshore Technical Community College	21%	$62,056	$76,849	Bogalusa, LA
Concorde Career College-Memphis	13%	$62,674	$71,343	Memphis, TN-MS-AR
Concorde Career College-Portland	13%	$62,962	$71,443	Portland-Vancouver-Hillsboro, OR-WA
Brookline College-Phoenix	12%	$62,337	$70,234	Phoenix-Mesa-Scottsdale, AZ
Vermont Technical College	12%	$62,535	$70,312	Claremont-Lebanon, NH-VT
San Joaquin Valley College-Visalia	11%	$63,537	$71,082	Visalia-Porterville, CA
Kaplan College-Sacramento	8%	$63,343	$68,934	Sacramento--Roseville--Arden-Arcade, CA
NHTI-Concord's Community College	8%	$60,545	$65,432	Concord, NH
Spartan College of Aeronautics and Technology	8%	$59,035	$63,729	Tulsa, OK
Madisonville Community College	7%	$61,496	$65,863	Madisonville, KY
Average for all four-year or higher colleges	2%	$62,160	$63,900	
Average of all two-year or lower colleges	-1%	$61,400	$60,600	

Source: Authors' analysis of various sources

Figure 8. Percent Increase in Occupational Earnings Power Beyond Predicted for One Standard Deviation in Quality Variable



Note: Light blue bar indicates that effect is not statistically different than zero at 95% confidence levels.
Source: Authors' analysis of various sources

Student loan repayment: The third value-added metric considers the probability of federal student loan repayment within the first three years of graduation. Unlike the other two measures, this measure focuses on the very early stages of graduates' careers and considers—in a sense—how student debt burdens interact with earnings. Recent graduates at the highest risk of default are those with low salaries and a high debt burden.

This measure is the least related to the other two, as the correlation coefficient is just 0.38 with value-added with respect to mid-career salary and 0.30 with value-added with respect to occupational earnings power. Meanwhile, the other two value-added measures show a correlation of 0.59.

Colleges with the highest value-added with respect to repayment (meaning default rates are less than predicted) tend to retain and graduate students at high rates, offer high-value curricula, and award generous financial support. These factors predict higher or lower default rates across institutions (Figure 9).

The list of top performers on value-added with respect to student loan repayment offers a number of surprises, and is distinct from the top performer list on other value-added variables. This suggests that colleges help reduce student loan default rates in a variety of ways, not only by enhancing earnings potential.

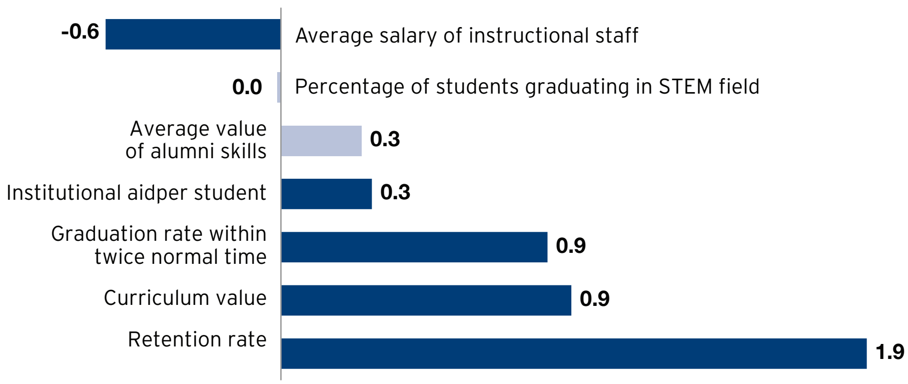
The three top-performing four-year colleges on value-added with respect to loan repayment score very highly on unobservable aspects of quality (Table 7). Brigham Young University shows up twice, once for its main campus in Idaho and again for its Provo campus. The very high repayment rates are not readily explained by observable characteristics. For other top-performing colleges, retention rates, graduation rates, and curriculum value account for most of the value-added. These factors explain the high performance of the Palmer College of Chiropractic, Grinnell, Notre Dame, Wesleyan, and Pomona, as well as Swarthmore and MIT, which fall just outside the top 10.

Table 7. Colleges With the Highest Value-Added With Respect to Loan Repayment, by Type of College

	Value-added	Predicted loan repay-ment	Actual loan repayment	Metropolitan area
Four-year colleges with highest value-added with respect to loan repayment				
Brigham Young University-Idaho	9.1	88.3	97.4	Rexburg, ID
Saint Johns University	9.1	89.6	98.7	St. Cloud, MN
Brigham Young University-Provo	8.8	90.0	98.8	Provo-Orem, UT
Palmer College of Chiropractic-Davenport	8.5	88.0	96.5	Davenport-Moline-Rock Island, IA-IL
Grinnell College	7.8	90.0	97.9	Grinnell, IA
University of Notre Dame	7.7	91.4	99.1	South Bend-Mishawaka, IN-MI
Wesleyan University	7.6	91.0	98.7	Hartford-West Hartford-East Hartford, CT
Carnegie Mellon University	7.6	91.2	98.8	Pittsburgh, PA
Pomona College	7.5	92.0	99.4	Los Angeles-Long Beach-Anaheim, CA
Polytechnic Institute of New York University	7.4	89.6	97.0	New York-Newark-Jersey City, NY-NJ-PA
Two-year colleges with highest value-added with respect to loan repayment				
Hutchinson Community College	11.7	81.3	93.0	Hutchinson, KS
Sandhills Community College	10.7	81.0	91.7	Pinehurst-Southern Pines, NC
Southern California Institute of Technology	10.3	76.9	87.2	Los Angeles-Long Beach-Anaheim, CA
Heald College-Fresno*	9.7	80.1	89.8	Fresno, CA
Vermont Technical College	9.5	84.3	93.8	Claremont-Lebanon, NH-VT
Lake Area Technical Institute	9.3	83.2	92.4	Watertown, SD
Latter-day Saints Business College	8.9	84.1	92.9	Salt Lake City, UT
American Career College-Los Angeles	8.8	80.9	89.7	Los Angeles-Long Beach-Anaheim, CA
North Dakota State College of Science	8.1	81.2	89.3	Wahpeton, ND-MN
Wyotech-Laramie	8.0	75.3	83.3	Laramie, WY
Average for all four-year or higher colleges	1.6	91.0	92.5	
Average for all two-year or lower colleges	-2.4	83.1	80.6	

** Heald College reported the same default information across all of its campuses, so the exact rate at each campus is not available. Its Fresno campus had the highest expected default rate, so it ranks the highest on value-added. The owners of Heald College have recently been forced to sell the institution.*
Note: Averages are weighted by number of students with loans.
Source: Authors' analysis of various sources

Figure 9. Percentage-Point Increase or Decrease in Loan Repayment Rate Beyond Predicted for One Standard Deviation in Quality Variable



Note: Light blue bar indicates that effect is not statistically different than zero at 95% confidence levels.
Source: Authors' analysis of various sources

The top scoring two-year colleges with respect to repayment rate value-added are Hutchinson Community College in Kansas and Sandhills Community College in Pinehurst, N.C. Neither score well, however, on quality measures predictive of success. On the other hand, observable quality measures explain much of the performance for the Southern California Institute of Technology, the Lake Area Technical Institute in South Dakota, Latter-Day Saints Business College in Utah, the American Career College-Los Angeles, and Wyotech-Laramie.

Compared to popular rankings, value-added measures more accurately predict student economic performance for students with similar characteristics.

The measures of curriculum value, percent graduating in a STEM field, alumni skills, graduation rate, retention rate, aid per student, and instructional staff salaries provide a new framework to think about a college's quality as distinct from its ability to attract top students. The biggest limitation of this approach, however, is that there are many student characteristics for which this analysis cannot account but that may influence students' eventual economic outcomes. For example, student grades, aspects of writing ability, leadership, and other less obvious traits may still correlate with college quality, even after controlling for student characteristics reported through IPEDS. A preferable approach would be to use richer student-level data and estimate school value-added using unmeasured aspects of college quality, as is done in teacher value-added models.[39]

While the results here may fail to meet an ideal standard for social science research, they can be compared favorably to existing college rankings. The most notable private rankings—issued by *U.S. News*, *Forbes*, and *Money*—tend to be highly correlated, but differences in criteria and weighting result in three distinct lists (Table 8). For example, Princeton and Stanford rank in the top five in all three lists, yet Brigham Young University is ranked 62nd by *U.S. News*, 79th by *Forbes*, and 9th by *Money*.

All of these lists, especially those from *Forbes* and *Money*, use sophisticated statistical techniques and meaningful criteria, but they have various problems. Most seriously, there is no sound theoretical basis behind the rankings, nor justification for the combinations and weighting of diverse metrics into singular measures of quality. Some of the metrics likely have no relation to objective outcomes. For example, both *U.S. News* and *Money* use class size as a factor, yet there is little social science evidence showing that smaller class sizes predict greater learning or success at the college level.[40] In other cases, important metrics may be combined in unusual ways that undermine their validity. *Forbes* and *Money* give weight to student debt, loan default rates, and earnings, but they do not consider how these interact: If students are earning high salaries and easily making loan payments, then an extra $40,000 in debt may be irrelevant to their quality of life.

Table 8. Comparison of Popular Rankings of Universities by Criteria Used

	U.S. News	*Forbes*/Center for College Affordability	*Money*
Subjective reputation	Yes	No	No
Graduation rate	Yes	Yes	Yes
Post-graduate success	No	Yes	Yes
Selectivity of school	Yes	No	Yes
Cost or student debt	No	Yes	Yes
Class size	Yes	No	Yes

Source: Authors' analysis of U.S. News, Forbes, and Money methodology summaries

Crucially, none of these rankings effectively isolates the college's contribution to student learning. *Money*, for example, uses some value-added measures that adjust for student selectivity, but in other metrics it gives schools credit for being more selective. Thus, its final ranking is a mix of both value-added measures and the selectivity of the school. Selectivity, measured by the admissions rate, is also directly included in the rankings by *U.S. News*. This fuels an absurd competition among schools, in which they advertise widely so as to encourage even unqualified students to apply, thereby driving down admissions rates.[41] *Forbes* does not directly include selectivity measures but does not adjust for them either. The result is that *Forbes* rankings are very similar to *U.S. News* rankings, and both reward colleges that admit students with the highest probability of career success.

The rankings introduced here make advances over these conventional rankings in two respects: availability of information, and accuracy at predicting alumni economic outcomes.

First, these value-added measures are widely available. The number of colleges for which value-added data are calculated here is double or triple the number of colleges with data from the *Forbes*, *Money*, and *U.S. News* rankings. An even broader and only slightly less robust measure of value-added with respect to repayment rates is available for 4,400 colleges. Moreover, some of the key quality factors—like curriculum value and STEM orientation of graduates—are available for all or nearly all of the 7,400 colleges in the United States.

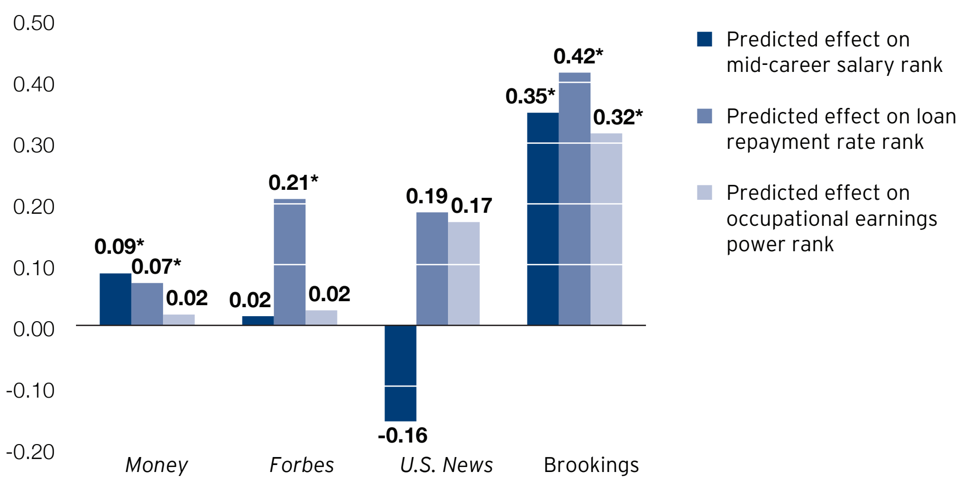
Second, the method used here yields more accurate measures of how schools affect student economic outcomes, given the characteristics of students. Imagine a model in which college rank on mid-career salaries is predicted based on the publication rank (e.g., *U.S. News* or *Money*) and relevant student and institutional characteristics (like share of awards given out to graduate students and test scores). Say school A is ranked number 1 and school B ranked number 11 by one of the publications. If a publication's rank matched real world outcomes perfectly, after adjusting for test scores and family income, then school A's value-added rank would be 10 places ahead of school B's, and a one-unit change in the average publication rank would predict a one-unit (1.00) change in the actual value-added rank.

In actual fact, a one-unit change in the *Money* rank predicts a significant but very small change of just 0.09 on earnings, conditional on the student and institutional characteristics used in the value-added model in this analysis. A one-unit change in the *Forbes* or *U.S. News* rank is even less predictive of alumni earnings and not statistically distinguishable from zero (0.02 and -0.16 on average), again controlling for these other factors. In each case, test scores and student characteristics are far more predictive of student earnings than the publication ranks, suggesting that the rankings have little to do with school quality independent of student characteristics.

By contrast, the same approach using the value-added measure derived here can explain much of the variation in salaries. A change in our ranking is associated with a 0.35 change, and the explanatory power is seven times larger than what the *Money* ranking provides.[42] In short, the value-added metrics developed here are much better at predicting variation in alumni salaries (Figure 10) across colleges with similar student test scores.

The results are similar using student loan repayment rates as the outcome of interest or occupational earnings power. A one-unit change in the Brookings value-added rank predicts a change in repayment rate rank of 0.42 and a change in occupational earnings power rank of 0.32. Both estimates are much more precise than the strongest popular ranking measure, which is *Forbes* in the first case and *U.S. News* in the second. For occupational earnings power, none of the popular measures are even significant at predicting better outcomes, after controlling for student test scores and the other measures.[43] Likewise, when included in the same predictive model separately with each of the other rankings system, our value-added rankings offer much greater explanatory power than the other rankings for each of the three outcomes. In fact, it is the only rank that predicts better outcomes.[44]

Figure 10. Predicted effect of moving up one rank (toward number one) in each of the four rankings systems on economic outcomes



Note: Coefficient of regression of overall or value-added college rank on outcome rank is shown.
** indicates that effect is statistically different than zero at 95% confidence levels or higher.*
Source: Authors' analysis of various sources

The fact that the value-added measures developed here are better at predicting the college's contribution to economic outcomes does not imply that they are more closely tied to student characteristics like test scores. Both the *U.S. News* and *Forbes* rankings relate very closely to test scores, with correlations of 0.89 and 0.82. The *Money* rankings, which use some value-added concepts, have a lower correlation of 0.57. Our value-added measures are closer to and even lower than the *Money* correlations: 0.56 for mid-career earnings, 0.49 for occupational earnings power, and 0.45 for repayment rates.[45] In this sense, the value-added approach creates some distance between student characteristics and college quality. While top-scoring students tend to go to high-value-added schools, the two concepts are not identical.

Conclusion

Higher education is enormously important to individual and collective prosperity. Yet escalating costs have created an urgent need for more and better information about the huge investment in time and money on the part of students, families, and taxpayers.

In this context, this report makes several contributions toward filling that information gap. First, the analysis demonstrates that there are more high-quality data on colleges than many people think. The data exist in different places, so that with considerable effort researchers can cobble the information together and present it in ways that are clear and useful to the public.

Second, it identifies a few factors that colleges can influence that seem to meaningfully affect alumni economic outcomes. These include completion rates, retention rates, the specific skills learned by alumni, the value of their curricula and STEM relevance, the salaries of their teachers, and the aid they give to their students. While college leaders may not fully control all these factors, most can enhance performance in these areas in ways that can benefit alumni economically and make positive contributions to the broader economy.

Third, the analysis demonstrates how one can measure the contribution that colleges make to graduates' economic outcomes, above and beyond what their backgrounds (i.e., test scores and other characteristics at the time of admission) would suggest. The college economic value-added metrics developed here have important limitations, but they are available for a world of community colleges and nonselective colleges that conventional rankings fail to explore. And the metrics more accurately predict economic outcomes than the popular rankings, calling into question whether the latter measure anything useful beyond student competence at the time of admission.

It is hoped that this report will spark further research on college performance. This method could be improved with better measures of student characteristics at the school level. Acknowledging that the best econometric model is unclear, these estimates might be improved by averaging across iterations of the value-added models, meaning that different combinations of control and quality variables could be used to predict student outcomes. Likewise, more accurate results may be achievable if the data used here were replaced with student-level data containing more precise measures of both economic outcomes and characteristics at the time of admission.

What can be done to increase college quality?

All of the precise mechanisms that make higher-quality schools better at graduating their students have not been identified, but there are a number of replicable programmatic features that distinguish colleges from one another. College administrators acting at the institutional level, or in conjunction with public-, private-, and civic-sector partners, can implement many of these features.

One clear finding is that colleges that succeed in helping more of their students graduate produce better economic outcomes for alumni. Financial aid, alone or in combination with social and academic support, advisement, and the accommodation of extra-academic student obligations, have proven effective in enhancing graduation from community and four-year colleges.[46] One program with these features at six City University of New York (CUNY) community colleges lifted three-year graduation rates from an associate's degree program from an estimated 20-25 percent to 55 percent, while serving mostly low-income Hispanic and black students, many with developmental education needs.[47]

Unfortunately, there is little evidence to suggest that other student support policies—including remediation—have much effect on student outcomes and graduation alone, though the evidence is inconsistent and mixed.[48]

This analysis also shows that a college's curriculum, in terms of its mix of majors and even the specific skills its instructors teach, can be hugely relevant to graduate success. This does not mean that liberal arts programs or those that train students for generally lower-paying fields are not valuable to individuals and society. There will always be a need for students to be trained across a broad range of disciplines, whose practical value lies beyond commercial profit alone. Yet students should be fully informed as to the realistic labor market potential for a major before committing so much of their time and money to pursuing one. Indeed, in a 2014 survey of incoming students at baccalaureate institutions, 86 percent of respondents said that being able to get a "better job" was "very important" in their decision to go to college, and 67 percent agreed with the statement, "The chief benefit of a college education is that it increases one's earning power."[49]

In the context of workforce development strategy, a number of state and local policy options are available to enhance curriculum value at colleges, which would lead to higher wages, tax revenues, and economic growth for regional economies. Florida, for example, has begun to reward public colleges for graduating more students in high-demand majors.[50] Governors of Pennsylvania and North Carolina are looking to increase funding for STEM education at regional community colleges.[51] An alternative or complementary approach would focus efforts on improving high school and earlier levels of STEM education, so students are more likely to choose and complete majors in high-paying fields. A recent Brookings report discusses a number of the relevant policy options to boost workforce readiness in STEM-oriented "advanced industries," and also points to an important role for private-sector organizations in partnering with local colleges.[52]

At the very least, more states and state boards of education can follow the leads of Texas, Florida, and a few other states in publishing data on student earnings by college in a transparent way that allows researchers and parents to readily compare colleges.

How should value added-measures like these be used?

The data and approaches developed in this report offer a starting point for more informed decision-making on behalf of stakeholders. Yet, they should not replace the more detailed judgments needed to make final decisions on issues such as where to attend college or how much public funding should be allocated to a university.

Start with parents and potential students. The data available on the Brookings website can be used to compare schools along a number of dimensions that are relevant to the future earnings of graduates, which may be useful in considering application and attendance decisions. When comparing two or more schools, the value-added metric could offer a useful nudge in one direction, even as cost, location, the availability of specific degree programs, and other factors would need to be considered.

College administrators and trustees could use these data to evaluate their institution's broad strengths and weaknesses so as to target further investigation and inquiry in to how to best serve their students. In some cases, poor results may be due entirely to an institutional legacy or mission that is largely incommensurate with the graduation of many high-earning alumni. Other schools may find there is more they can do without sacrificing their core mission.

Public officials could use these data to broadly observe which schools are failing to deliver and which are outperforming their peers. It would be a mistake to allocate public resources (or even private donations) based entirely on econometric results such as these, but these data can provide initial guidance into which schools bear further scrutiny and may lead to targeted support of and new investments in failing schools so they can better serve the public. Likewise, high-performing colleges may offer important lessons as to what institutional-specific programs and initiatives can be replicated elsewhere.

B

Technical Appendix

This document describes the methods used to generate the statistics and analytic findings discussed in the report. It is organized as follows:

1. Calculation of curriculum value
2. Classification of STEM majors
3. LinkedIn data and assessment of bias
4. Construction of value-added metrics
5. Empirical analysis of economic outcomes
6. Discussion of models' strengths and weaknesses
7. Empirical comparison with popular rankings

1. Calculation of curriculum value

Curriculum value is the average median-salary-by-field for each institution weighted by the number of graduates in each field.

This is expressed in equation 1, where V is median earnings by field of study (or CIP code, referring to the U.S. Department of Education's system known as the Classification of Instructional Programs) for all workers (in the labor market) in 2013, using IPUMS data; n is the number of graduates from institution i in field f.

$$(1)\ Curriculum\ value_i = \sum_{f=1}^{f=x} \left[V_f \frac{n_{i,f}}{n_i} \right]$$

In practice, curriculum value is measured less accurately for sub-bachelor's degree holders, since the Census Bureau collects data only on the bachelor's degree field of study.[53] To roughly assess the level of this bias, we calculated the actual distribution of associate's degree awards by field of study using IPEDS data for every institution. We then matched census CIP fields to IPEDS CIP fields. The census fields were somewhat broader or more general. We were able to match most associate's degree awards to a field that had census data. In fact, 97.5 percent of 2012-2013 graduates from an associate's degree or lower program could be matched to a corresponding census CIP field with non-missing earnings data.

These matches appear to be accurate. PayScale reports earnings by both field of associate's and bachelor's degree. The correlation between the PayScale median earnings for associate's degree fields and the census-based median earnings by field is 0.76. This is only slightly lower than the PayScale bachelor's degree field correlation with census-based earnings by field: 0.85. For every dollar increase in PayScale associate's degree earnings, the census-based earnings by field measure increases by $1.06, with a t-statistic of 9.6. Finally, PayScale earnings by field for associate's degree holders is highly correlated with PayScale earnings by field for bachelor's degree holders (0.87). We conclude that earnings by field of study for bachelor's degree holders accurately proxy for earnings by field of study for associate's degree holders.

2. Classification of STEM majors

The vast array of majors requiring various levels of technical and quantitative sophistication makes deeming fields as STEM more challenging than one might think. Therefore, to provide a more rigorous foundation for whether STEM skills are being taught at a college, we took advantage of O*NET resources.

O*NET, a Department of Labor-funded project intended to provide rich data on occupations, provides two datasets of interest here: a crosswalk between detailed field-of-study codes (CIPs) and the occupations (or standard occupational classification system codes, known as SOCs) that those instructional programs prepare students to enter; and a survey of the knowledge requirements of every occupation.

The knowledge survey asks participants to assess their level of knowledge across many domains on a 1-7 scale, with anchors to assist their answers. We focus on biology, chemistry, computers and electronics, engineering and technology, mathematics, and physics. We have used and described this survey in more detail in a previous work.[54] For each knowledge domain, we first calculate the mean level of knowledge across all occupations. Then we subtract the mean score from the actual score for each occupation. This adjusts the knowledge level for different domains to their relation to the mean occupation. We match these occupational knowledge scores to fields of study using the O*NET crosswalk.[55]

Next, for each CIP field, we calculate the mean-adjusted knowledge level for each domain. We then standardize each domain to have a standard deviation of one and mean of zero. Finally, we consider a field of study to be a STEM-CIP if it scores a one or higher on this standardized scale on at least one of these six knowledge domains. *Thus, a STEM field is one in which students are trained for an occupation or multiple occupations that require a high level of knowledge in at least one of the six core STEM domains.*

The SOC-CIP crosswalk was last updated in 2010. Perhaps because of that and other methodological challenges, 18 percent of six-digit CIP fields (251 of 1416) could not be matched to knowledge scores. To avoid missing data, scores for broader aggregation were imputed. In most cases (179), four-digit scores could be imputed to the six-digit CIP major. For others, the imputation was at the three-digit level (36) or two-digit level (22). Some military-specific fields could not be matched to knowledge scores because O*NET does not collect data on military-only occupations. These were deemed non-STEM for the purposes of this report.

In practice, the results mostly mirror what is typically considered STEM (see Appendix Table 1 for a high-level summary). All majors within the broad families of engineering, biology, and math qualify as STEM using these criteria. At least 90 percent qualify for physical sciences, engineering technologies, architecture, and computer science. This method proves especially valuable in the more ambiguous cases, such as agriculture, interdisciplinary studies, science technicians, health, communications technologies, mechanic and repaid technologies, education, and business. Within these and other majors, only the most STEM-focused majors qualify, so the majors in these families that are light on core sciences or technical knowledge do not make it.

A few examples illustrate how this method plays out. Within computer science, all but "data entry" and "word processing" qualify as STEM. Within health care, "registered nursing" meets the criteria but not "nursing assistant." For precision production majors, "machine tool technology" and "computer numerically controlled" majors are deemed STEM, but not ironworking or woodworking. Economics qualifies within social science, but not political science, sociology, or criminology. Linguistics is the only discipline within language study to qualify.

This method does not shut out the arts. Indeed, in visual and performing arts, "illustration" qualifies based on the engineering knowledge required for the occupations for which it prepares students (like set design). "game and interactive media design," "music theory," and "digital arts" also count as STEM because their career paths require high levels of computer knowledge, according to O*NET data.

This definition proved to more robustly explain student outcomes in our subsequent models than a more simplistic definition based on two-digit family codes typically considered STEM. Overall, 41 percent of majors are deemed STEM using this method but only 28 percent of awards are actually given out in STEM fields. The full six-digit list is available upon request.

B

Appendix Table 1. Percentage of Majors Classified as STEM by Two-Digit CIP Family			
CIP family	Family title	Percent of majors deemed STEM	Number of STEM awards granted in 2012-2013
14	Engineering	100%	145,318
26	Biological and biomedical sciences	100%	132,333
27	Mathematics and statistics	100%	34,879
40	Physical sciences	98%	43,143
15	Engineering technologies and engineering-related fields	97%	87,394
4	Architecture and related services	91%	19,037
11	Computer and information sciences and support services	90%	146,192
3	Natural resources and conservation	86%	24,236
1	Agriculture, agriculture operations, and related sciences	69%	26,195
41	Science technologies/technicians	67%	3,089
51	Health professions and related programs	47%	427,236
10	Communications technologies/technicians and support services	47%	14,612
47	Mechanic and repair technologies/technicians	44%	42,879
30	Multi/interdisciplinary studies	38%	16,697
46	Construction trades	35%	5,415
19	Family and consumer sciences/human sciences	33%	11,959
48	Precision production	33%	6,031
25	Library science	25%	434
49	Transportation and materials moving	24%	3,556
45	Social sciences	23%	38,315
43	Homeland security, law enforcement, firefighting, and related protective services	23%	12,990
52	Business, management, marketing, and related support services	18%	87,106
12	Personal and culinary services	13%	2,016
31	Parks, recreation, leisure, and fitness studies	8%	22,233
13	Education	8%	30,197
38	Philosophy and religious studies	8%	15
50	Visual and performing arts	6%	5,895
16	Foreign languages, literatures, and linguistics	2%	249
42	Psychology	0%	0
24	Liberal arts and sciences, general studies, and humanities	0%	0
39	Theology and religious vocations	0%	0
23	English language and literature/letters	0%	0
54	History	0%	0
29	Military technologies and applied sciences	0%	0
44	Public administration and social service professions	0%	0
5	Area, ethnic, cultural, gender, and group studies	0%	0
22	Legal professions and studies	0%	0
9	Communication, journalism, and related programs	0%	0

3. LinkedIn data and assessment of bias

To quantify the value of alumni skills that LinkedIn profile holders list on their resumes (or profiles) by institution, this study matches those skills to data obtained from Burning Glass, a labor market intelligence company.

LinkedIn data were obtained from the various college profile pages on the LinkedIn website, which are available to anyone with a LinkedIn account. Due to the difficulty of processing so many web pages, this study prioritized the largest colleges (by enrollment) and gathered as many schools as time and funding constraints would allow. In principle, data for nearly every college are available and could be used in subsequent work.

As described in previous Brookings research using the same database, Burning Glass has made available job-openings-level data for every vacancy posted online during 2013.[56] Of the 20 million vacancies, 3 million (or 15 percent) list salary data, as well as various skill requirements. If a salary range is offered, the minimum and maximum are divided by two to calculate a mean salary.

There are 8,735 distinct skills in the Burning Glass database, with an average number of job openings of 3,361 per skill. Skills are quantified by computing the average salary for each skill. For example, if 100 ads listed the programming language "Java" and 50 offered a salary of $100,000 and 50 offered a salary of $50,000, Java would get an average value of $75,000. The actual unweighted mean salary for all skills is $67,443.

There are 1,113 unique skills in the LinkedIn database. Among the top 25 most common skills for each school, 381 could be matched exactly without changing spelling. The rest were matched by making minor adjustments to the spelling or applying the closest matching concept, if available. Using the same method, data on Burning Glass certifications, an alternative to skills that applied more precisely in some cases, were used to replace salary measures for 90 missing values. Some skills, a total of 243, could not be matched and were too broad or ambiguous to match with a change of spelling (e.g., "security clearance"). For the average college, 86 percent of alumni skills were matched.

Since LinkedIn has not been used by many social scientists, it is unclear how well data derived from it accurately measure college graduate outcomes. As of the time of this writing in late 2014, LinkedIn has 99 million U.S. user profiles. If there are no duplicates, this suggests that 31 percent of the U.S. population has a LinkedIn profile. That is not entirely implausible, since users as young as 14 years old are officially eligible to have an account, according to the LinkedIn user agreement. Previous research estimates that 80 percent of IT professionals have LinkedIn profiles.[57] Likewise, a Pew Survey from 2013 found that 22 percent of Internet users report using LinkedIn.[58]

We made an attempt to calculate the bias by major using LinkedIn as a source by taking advantage of the fact that both LinkedIn and IPEDS report the number of graduates by major for schools. Appendix Table 2 lists two-digit major categories sorted by the largest proportional bias in terms of overrepresentation on LinkedIn. The blue-collar trade majors were relatively underrepresented.

To quantify the value of this bias at the school level, the average earnings of U.S. residents in the labor force with bachelor's degrees age 25-64 were calculated by two-digit field of study, using census microdata from IPUMS USA. These average earnings were imputed to school two-digit CIP fields for the LinkedIn distribution and IPEDS distribution. A weighted average value was then calculated for the LinkedIn sample and all graduates as reported by IPEDS. Average field-of-study earnings for the LinkedIn sample were divided by average field-of-study earnings for the IPEDS sample, yielding a measure of bias. This is used in the analysis of value-added below to adjust the predicted outcomes.

For the average college, people with LinkedIn profiles held majors in fields that paid 14 percent higher than the fields in which graduates from the 2012-2013 year held majors. The profile-weighted average was 33 percent, meaning that the average LinkedIn user reports having majored in a field of study that pays 33 percent higher than all alumni from his or her college for the most recent year. It is notable that the bias was significantly lower at primarily two-year colleges than primarily four-year colleges—13 percent versus 36 percent. One source of error in these estimates is that earnings for two-year graduates by field of study are not available from the census, so data from bachelor's degree earners from the same major had to be imputed.

The distribution of the bias is shown in Appendix Figure 1. For 27 percent of the 2,163 colleges for which we have data, the bias falls within plus or minus 10 percent. For 58 percent, the bias falls within plus or minus 25 percent. The bias is outside 50 percent for 16 percent of colleges.

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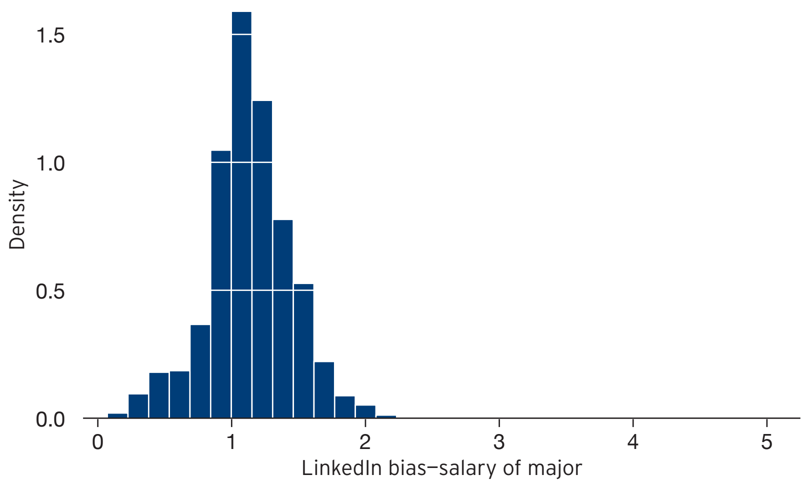
Appendix Table 2. Over/Underrepresentation of People by Field of Study in LinkedIn Compared to School's Recent Cohort of Graduates				
Major	**IPEDS share of graduates, 2012-2013**	**LinkedIn share of profiles**	**LinkedIn share - IPEDS share**	**LinkedIn share/ IPEDS share**
Area, ethnic, cultural, gender, and group studies	0.2%	0.9%	0.7%	3.9
Communication, journalism, and related programs	3.0%	7.3%	4.3%	2.4
Philosophy and religious studies	0.1%	0.3%	0.2%	2.3
Engineering	4.4%	9.7%	5.3%	2.2
Architecture and related services	0.3%	0.6%	0.3%	1.8
Physical sciences	1.0%	1.8%	0.8%	1.8
Computer and information sciences and support services	3.7%	6.4%	2.7%	1.7
Business, management, marketing, and related support services	21.1%	34.5%	13.5%	1.6
Social sciences	6.0%	9.8%	3.8%	1.6
History	0.7%	1.1%	0.4%	1.6
Parks, recreation, leisure, and fitness studies	1.4%	2.1%	0.6%	1.4
Transportation and materials moving	0.1%	0.1%	0.0%	1.4
English language and literature/letters	1.9%	2.6%	0.6%	1.3
Mathematics and statistics	0.2%	0.3%	0.1%	1.3
Natural resources and conservation	0.2%	0.3%	0.0%	1.2
Visual and performing arts	3.9%	4.7%	0.7%	1.2
Foreign languages, literatures, and linguistics	0.0%	0.0%	0.0%	1.1
Multi/interdisciplinary studies	2.4%	2.5%	0.1%	1
Psychology	4.7%	4.2%	-0.5%	0.9
Library science	0.1%	0.1%	0.0%	0.9
Legal professions and studies	1.3%	0.9%	-0.4%	0.7
Public administration and social service professions	1.4%	0.6%	-0.7%	0.5
Agriculture, agriculture operations, and related sciences	0.5%	0.2%	-0.2%	0.5
Theology and religious vocations	0.3%	0.2%	-0.2%	0.4
Communications technologies/technicians and support services	0.1%	0.0%	-0.1%	0.4
Family and consumer sciences/human sciences	0.1%	0.0%	0.0%	0.4
Education	9.1%	3.1%	-6.0%	0.3
Biological and biomedical sciences	0.3%	0.1%	-0.2%	0.3
Liberal arts and sciences, general studies and humanities	11.7%	3.0%	-8.7%	0.3
Engineering technologies and engineering-related fields	1.0%	0.3%	-0.8%	0.2
Homeland security, law enforcement, firefighting, and related protective services	2.3%	0.5%	-1.8%	0.2
Personal and culinary services	0.9%	0.1%	-0.7%	0.2
Science technologies/technicians	0.0%	0.0%	0.0%	0.1
Health professions and related programs	14.4%	1.7%	-12.7%	0.1
Mechanic and repair technologies/technicians	1.0%	0.0%	-0.9%	0
Precision production	0.1%	0.0%	-0.1%	0
Construction trades	0.1%	0.0%	-0.1%	0

Appendix Figure 1. Distribution of LinkedIn Bias Across Colleges



Occupational earnings power

For each school with a profile, LinkedIn also provides data on the 25 most common occupations of LinkedIn users. We impute salaries to those fields using data from the 2013 Occupational Employment Survey from the U.S. Bureau of Labor Statistics. We use this information to measure *occupational earnings power.*

Complicating this exercise, LinkedIn groups occupations at a very high level that does not readily align with the SOC system used by the Bureau of Labor Statistics. We focus on 35 distinct occupational categories for which at least 1,000 user profiles exist. The most common occupation is "education." Rather than assign this (or other occupations) to one SOC category, we chose the most relevant three-digit "minor" classifications. For education, this included postsecondary teachers; preschool through high school teachers; other teachers; librarians; and other education, training, and library occupations. We calculated average 2013 salaries for the United States across these occupational groups, using the number of workers in those occupations as the weight.

For other categories, the match was easier. Engineering was matched to the occupational category for "engineers." "Finance" could be matched to the BLS minor group "financial specialists." The most difficult may have been the LinkedIn occupation "research." For this, we focused on the occupations most likely to be doing corporate, academic, or policy research: scientists, social scientists, postsecondary teachers, computer occupations, mathematicians, and engineers.

4. Construction of the value-added metrics

As discussed in the introduction to this report, colleges differ significantly in terms of the earnings potential of their students. So-called "selective" colleges intentionally admit only or mostly students they believe will be successful along social dimensions that include earnings power, entrepreneurial success, or leadership. Standardized test scores are one criterion these schools use to identify such students, but these scores are not available for most community colleges and even for some four-year colleges.

To preserve the predictive value of student test scores, we impute estimated test scores to missing observations based on the following model. Test scores are predicted based on tuition; the average amount of aid per student from the Pell grant program (which is only available to low-income students); the percent of students receiving no financial aid; the percent of students receiving aid from the college; the percent of students receiving federal student loans; the racial and foreign-born demographics of the student body (since schools with more Asian-Americans and foreign-born students

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Appendix Table 3. Regression of Standardized Math Scores on Student and School Data	
	Average standardized math score of admitted students
Local price index 2012	-0.00597***
	(0.00139)
Offers students remediation services	-0.189***
	(0.0273)
Offers students job placement services	0.113***
	(0.0328)
Accepts high school credit via advanced placement	-0.422***
	(0.115)
Gives credit based on prior learning or experience	-0.0993***
	(0.0248)
Percent of students receiving federal loans	-0.00787***
	(0.000866)
Percent of undergraduates not receiving any aid	0.00862***
	(0.00166)
Percent of undergraduates receiving aid from college	0.00266**
	(0.00119)
Published in-district tuition and fees 2013-2014	1.35e-05***
	(2.91e-06)
Average aid per recipient from any source	1.70e-05***
	(3.78e-06)
Ln of Pell grant aid per student	-0.621***
	(0.0491)
White student share of enrollment	0.772***
	(0.113)
Black student share of enrollment	-0.0311
	(0.115)
Foreign-born student share of enrollment	1.708***
	(0.282)
Asian student share of enrollment	3.360***
	(0.322)
Average age of enrolled students	-0.0165***
	(0.00478)
Female share of students	-0.727***
	(0.0993)
Mostly bachelor's-degree-granting college	0.0777
	(0.0833)
Mostly master's-degree-granting college	0.106
	(0.0957)
Mostly doctorate- or professional-degree-granting college	0.177
	(0.255)
Carnegie classification as associate's	-0.878***
	(0.122)
Carnegie classification as associate's under four-year college	-1.062***
	(0.225)
Carnegie classification as four-year but primarily associate's granting	-1.324***
	(0.253)
Carnegie classification as doctoral granting	-0.357***
	(0.0618)
Carnegie classification as master's college	-0.442***
	(0.0404)
Carnegie classification as baccalaureate college	-0.599***
	(0.0438)
Carnegie classification as theological college	-0.774***
	(0.0913)
Carnegie classification as professional college	-0.406***
	(0.0842)
Carnegie classification as arts college	-0.859***
	(0.0944)
Carnegie classification as nonaccredited	-0.718***
	(0.115)
Constant	5.773***
	(0.421)
Observations	1,393
Adjusted R-squared	0.824
Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1	

tend to have higher test scores); the female share of students; the student-faculty ratio; the school's retention rate (students admitted into less-selective schools have less incentive to stay); whether the school offers remediation classes; whether the college offers job placement services for alumni; whether the school's modal degree is less than a four-year degree, a four-year degree, or a graduate degree; the average age of students (since the most selective schools cater to young people who went straight from high school to college); the Carnegie basic classification (re-aggregated to fewer categories); and the average level of student aid, which can be used to attract better-prepared students.

The results of this regression are shown in Appendix Table 3. Higher tuition and aid variables predict higher test scores. Remediation offerings predict lower scores, as does Pell grant aid and the share of students taking out federal loans, which both indicate lower levels of family income. Colleges with higher shares of Asian and foreign-born student shares have higher predicted scores.

This test score model explains over three-quarters of the variation in test scores for the 1393 schools that had data for all fields. The "impute" command was used in STATA to calculate the predicted scores of colleges with missing test score data.[59]

With test score data and other metrics, we then modeled student outcomes with respect to PayScale and federal student loan default rates. The model takes the following form:

$$(2)\ Y_{c,r} = \alpha + \beta_1 S_{c,r} + \beta_2 C_{c,r} + \beta_3 P_r + \beta_4 Q_{c,r} + \mu_c$$

Student outcomes (Y) for a given college, c, in a given region, r, measured in terms of earnings or default rates, are a function of the college's average student characteristics (S), which are measured in terms of demographics, test scores, and eligibility for federal need-based aid (the Pell grant specifically), and characteristics of the college (C), measured by modal level of degree granted, percent of degrees given at various award levels, online status, and Carnegie classification.[60] P refers to location-specific variables. We include a metropolitan-specific price index, which is determined by the overall level of labor productivity, land regulations, and value of amenities in the area.[61] State fixed effects are included in this term as well.

The price index term is meant to capture the fact that employment opportunities will vary across regional labor markets, and students graduating from community colleges and even universities in "hotter" labor markets will find it easier to land higher-paying jobs, conditional on ability. Labor market opportunity is proxied through regional price parities, which are taken from the Bureau of Economic Analysis (BEA) and are available for every metropolitan area as well as nonmetropolitan areas of states. We assigned the average nonmetropolitan state price index to schools that did not exist in a metropolitan area, and we assigned the state metropolitan price index to schools that were in metropolitan areas but did not have BEA data.

The final term (Q) is meant to capture school quality measures unrelated to student characteristics, such as the value of skills taught, the relevance of the curriculum or mix of majors to market demand, the STEM orientation of the mix of majors, faculty salary, the graduation rate, the retention rate, and student aid.

The error from equation 2 can be thought of in the following way:

$$(3)\ Y - \widetilde{Y}_2 = u_c$$

Here $\widetilde{Y}$ is the predicted outcome (say earnings of attendees) from the model in equation 2 and Y is the actual outcome.[62] We assume that μ is uncorrelated with Q. Our main analysis tests the null hypothesis that Q is equal to zero. If the null hypothesis is rejected, we can conclude that Q contributes to the school's value-added with respect to student earnings.

Yet, we also want to calculate the school's actual value-added directly and in a way that allows Q to affect the measure. u_c has zero correlation with Q by assumption, so this would not work as a measure of value-added. One approach to calculating value-added would be to re-estimate equation 2 with Q omitted. In this way, Q would be correlated with the error term (or value-added metric). In practice, this presents a problem that makes it unworkable. Q is also highly correlated with S, C, and P. Indeed, omitting Q not only lowers the model's fit but increases the size of the coefficients β_1, β_2, and β_3. This suggests that excluding Q biases the estimated coefficients on those other variables and hence biases the error term from such an exercise, obscuring the true relationship between Q and value-added. This will be discussed in more detail below.

For that reason, we want to calculate a new residual, ϵ, that is purged of student characteristics predictive of future earnings but that contains school-level quality measures, in so far as they matter. To do this, we take the coefficients from equation 2 and recalculate Y, except we replace actual values of Q with mean values of Q or $\bar{Q}$. In effect, we calculate the following formula:

$$(4)\ \ Y_{c,r} = \alpha + \beta_1 S_{c,r} + \ \beta_2 C_{c,r} + \beta_3 P_r + \beta_4 \bar{Q} + \ \epsilon_{\ c}$$

In this case, $\bar{Q}$ is the mean for each of these quality measures, and the residual, ϵ, is related to μ in the following way:

$$(5)\ \ \ \epsilon - \mu = \beta_4 (Q - \bar{Q})$$

$$\epsilon = \beta_4\ (Q - \bar{Q}) + \ \mu$$

Because everything else is held constant, this is the same as the following:

$$(6)\ \ \ \epsilon = \left(\tilde{Y}_4 - \tilde{Y}_2\right) + \ \mu$$

In words, equation 5 five states that the residual, ϵ or unexplained student earnings, equals the difference between observed school quality measures and mean school quality measures plus any unmeasured aspects of value, captured in μ. This is our measure of *value-added*.

To elaborate, it takes the unexplained variation from our "best" regression μ and adds to it the difference between actual school quality and mean school quality. Equation 6 makes explicit that this is equal to adding the residual from equation 2 to the difference in predicted outcomes from the two equations. Stated otherwise, the extra earnings generated from the school's curriculum, teaching staff, and student support programs, insofar as they have any average effect, can be added to the unexplained earnings to get the school's value-added to student earnings.

In practice, the calculation of ϵ is rather simple. We estimate equation 2 to get the β_4 coefficients and add them to μ. That allows us to calculate a predicted outcome, $\tilde{Y}_4$, with the correct coefficients. ϵ is just the difference between actual Y and $\tilde{Y}_4$, and we derive it separately in different regressions for our outcomes of interest.

In data made available online, we will decompose (β_4 Q) and μ, so that, for each school, the relative contributions to value-added can be explicitly considered. Since the Q variables are standardized to have mean zero in the analysis, it is computationally very simple to make value-added the sum of each β_4 Q combination (there are seven in the main model) and μ.

5. Empirical analysis of economic outcomes

Drawing on this framework, we next investigate the determinants of value-added, focusing on seven core predictive measures that we regard as partly under the control of colleges: curriculum value, value of alumni skills, STEM orientation of degree programs, aid to students, faculty salaries, and graduation rates. That is, we estimate equation 2. The results are summarized in Appendix Table 4.

In the case of PayScale earnings, all of the main explanatory variables (which are standardized to have a standard deviation of one to facilitate comparison) are significant in the expected direction, with the exception of instructor salaries, which is negative and insignificant.

These results provide clear evidence that factors that are at least somewhat under the control of colleges are consistently associated with higher student salaries after graduation, even controlling for student test scores, income, and institutional characteristics. The models explain roughly 84 percent of the variation across the 1,139 colleges with all the data.

Model 2 analyzes occupational earnings power of alumni with LinkedIn profiles. Instructor salaries, curriculum value, and alumni skills predict employment in higher-paying occupations. Student aid predicts lower-paying occupations (perhaps because students feel less worried about pursuing high-paying careers to pay back loans). It is worth pointing out that the LinkedIn skills have a very strong relationship with LinkedIn occupations, but some of the skills listed by LinkedIn are likely to be acquired on the job, which should increase the correlation between the two measures.

Models 3 and 4 analyze default rates first in the most fully specified model and then in one that drops alumni skills, the LinkedIn bias variable, and faculty salary, because those variables are not observed for many colleges. Both models, especially the first, maintain very high adjusted R-squares of 0.82 and 0.58.

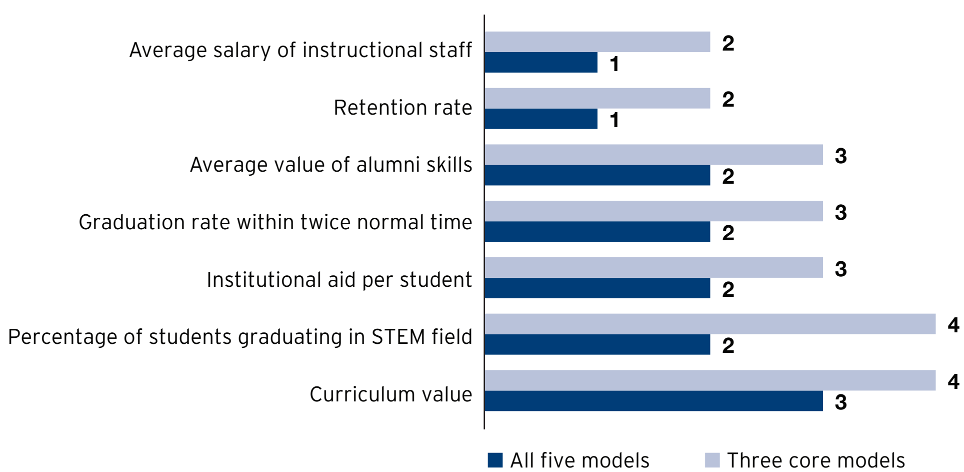
The results from model 3 are in accord with the previous findings in that the graduation rate, curriculum value, and student aid levels all predict lower default rates. In model 4, only the graduation rate and student aid levels are significant, but if the STEM share is also excluded, curriculum value remains significant in the expected direction. Alumni skills are omitted.

The final model looks at salary data again but only for four-year colleges and uses salaries from all graduates. Student aid, faculty salaries, alumni skills, and curriculum value are all strongly related to future earnings, confirming earlier results.

To simplify the presentation of the results, Appendix Figure 2 summarizes the robustness of the results across the seven quality measures. It ranks them by the number of models in which each is significant in the expected direction. Of the two weakest, the retention rate is significant in predicting default rates (in both models), and teacher salary is significant in the "right" direction in predicting occupational earnings and salaries from all graduates. Three variables are significant in the expected direction in two of the three core models and three of the five total models: alumni skills, the graduation rate, and institutional aid. The STEM share of graduates is significant in two of the three core models and both of the alternative specifications. Curriculum value is the most robust: significant in the three core models and all but the broadest default rate model, when the STEM share is included.

These results were generated treating each institution as equally important in the analysis. Another approach may give more weight to larger institutions and weigh the coefficients by student enrollment. This was rejected as a first choice because large public universities or community colleges would determine much of the outcomes, without perhaps providing accurate information about small colleges. Still, the results are available upon request and are broadly similar. In fact, the adjusted R-squared values are even higher for all but model 5—and much higher for model 4 (up to 0.82 from 0.58). In the first model, the retention rate becomes significant in predicting salaries. Curriculum value and alumni skills are highly significant in the expected direction in each model.

Appendix Figure 2. Summary of Regression Results for Quality Metrics



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Appendix Table 4. Regression of Quality, Student, and School Characteristics on Alumni Economic Outcomes					
	Ln mid-career earnings	Occupational earnings power	Default rate	Default rate	Ln mid-career earnings, all graduates
	1	3	2	4	5
Local price index 2012	0.00285***	-0.000197*	-0.0632***	-0.0704***	0.00152***
	(0.000465)	(0.000114)	(0.0138)	(0.0142)	(0.000528)
Modal degree level is two year	0.0100	-0.00669	-0.677	0.0901	
	(0.0272)	(0.00475)	(0.613)	(0.452)	
Modal degree level is bachelor's	0.0920	-0.0162	0.771	-0.643	
	(0.0776)	(0.0106)	(1.306)	(0.765)	
Modal degree level is master's	0.110	-0.0158	0.706	-0.723	0.0169
	(0.0789)	(0.0113)	(1.383)	(0.908)	(0.0161)
Modal degree level is doctorate or professional		0.0469*	2.531	0.591	
		(0.0245)	(2.935)	(1.658)	
Online only enrollment	0.0815	-0.0194	0.221	-1.226	0.0832
	(0.0710)	(0.0137)	(1.642)	(2.082)	(0.0725)
Percent of students enrolled part time	0.0812**	-0.00541	-1.133	-1.594***	0.0922**
	(0.0333)	(0.00686)	(0.847)	(0.537)	(0.0380)
Percent of freshman from same state	-0.0539**	-0.00871*	-1.511***	1.134**	-0.0668***
	(0.0215)	(0.00465)	(0.574)	(0.526)	(0.0239)
Foreign-born student share of enrollment	-0.196**	0.0865***	-1.937	0.471	-0.246***
	(0.0855)	(0.0176)	(2.320)	(2.184)	(0.0920)
Asian student share of enrollment	0.236***	0.0128	-8.663***	-6.235***	0.225**
	(0.0883)	(0.0197)	(2.371)	(2.334)	(0.104)
White student share of enrollment	0.00566	-0.00478	-4.170***	-3.343***	-0.0786**
	(0.0262)	(0.00564)	(0.697)	(0.553)	(0.0322)
Average age of students	-0.0110***	0.000865**	0.00719	0.184***	-0.0115***
	(0.00177)	(0.000363)	(0.0449)	(0.0308)	(0.00209)
Female share of students	-0.211***	-0.0456***	-6.803***	-7.764***	-0.192***
	(0.0391)	(0.00803)	(0.969)	(0.552)	(0.0443)
Percent of students receiving no aid	0.000548	0.000146*	0.00402	0.0129	0.000711
	(0.000364)	(7.97e-05)	(0.0100)	(0.00892)	(0.000467)
Ln Pell grant aid per student	-0.0562***	0.00764***	2.387***	1.424***	-0.0938***
	(0.0129)	(0.00283)	(0.355)	(0.301)	(0.0161)
Percent of students receiving federal loans	-0.000803***	-1.76e-05	0.00537	-0.0199***	-0.000949***
	(0.000241)	(5.06e-05)	(0.00647)	(0.00580)	(0.000309)
LinkedIn salary bias	-0.00484	0.00593**	0.720*		0.0327*

6. Discussion of models' strengths and weaknesses

As discussed in the main body of the report, the value-added calculations here outperform standard rankings of colleges along two very important dimensions: They are more widely available and thereby not limited to only a small percentage of colleges, and they are more accurate, in that they are less biased by student and college selection and yet more predictive of actual economic success post-graduation. By combining many different databases and controlling for a long list of significant variables, the analysis attempts to mitigate selection bias and isolate aspects of student success that are under the college's control.

Still, if those are this method's strengths, it nevertheless has a number of weaknesses.

For one, the results are still burdened by the fact that students and colleges select students based, in part, on earnings potential, since the latter is correlated with things observable to the admissions committee like grade point average, recommendation letters, and test scores. The quality measures

Appendix Table 4 (cont.). Regression of Quality, Student, and School Characteristics on Alumni Economic Outcomes

	Ln mid-career earnings	Occupational earnings power	Default rate	Default rate	Ln mid-career earnings, all graduates
	(0.0146)	(0.00281)	(0.370)		(0.0174)
Imputed standardized math scores (standardized)	-0.0178*	0.00831***	-0.485	-1.414***	-0.00672
	(0.0102)	(0.00248)	(0.299)	(0.308)	(0.0112)
Imputed standardized math scores (standardized)^2	0.0119***	0.00307***	0.262***	0.240***	0.00159
	(0.00283)	(0.000677)	(0.0824)	(0.0860)	(0.00347)
Retention rate (standardized)	0.0112	0.00312*	-1.868***	-0.984***	0.00794
	(0.00897)	(0.00159)	(0.195)	(0.114)	(0.0127)
Institutional aid per student (standardized)	0.0106**	-0.00205**	-0.290**	-0.00449	0.0124***
	(0.00422)	(0.00103)	(0.125)	(0.129)	(0.00449)
Average salary of instructional staff (standardized)	0.00396	0.00792***	0.559**		0.0319***
	(0.00888)	(0.00188)	(0.234)		(0.0116)
Ln average value of alumni skills (standardized)	0.0297***	0.0248***	-0.257		0.0330***
	(0.00633)	(0.00135)	(0.164)		(0.00716)
Percentage of students graduating in STEM field (standardized)	0.0354***	0.0150***	0.0123	-0.750***	0.0261***
	(0.00876)	(0.00177)	(0.216)	(0.132)	(0.0100)
Ln curriculum value (standardized)	0.0688***	0.00501**	-0.926***	-0.0250	0.0745***
	(0.0136)	(0.00245)	(0.303)	(0.154)	(0.0159)
Graduation rate within twice normal time (standardized)	0.0224**	0.000622	-0.850***	-0.972***	0.0139
	(0.0108)	(0.00196)	(0.240)	(0.147)	(0.0145)
Constant	11.55***	11.11***	11.98**	6.627	11.93***
	(0.168)	(0.0401)	(4.875)	(6.512)	(0.190)
F-statistic on state fixed effects	2.2	2.5	5.1	4.6	2.7
F-statistic on student effects	17.6	18.1	29.9	56.4	17.8
F-statistic on graduate shares by degree level	1.6	3.7	8.3	9.1	1.6
F-statistic on Carnegie classifications	2.6	4.4	3.4	6.0	1.6
Observations	1,139	1,867	1,785	4,400	859
Adjusted R-squared	0.840	0.724	0.823	0.579	0.778

*Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. All regressions include control variables for the basic Carnegie classification categories, state fixed effects, and the percentage of graduates from each degree level. F-statistics shown above. In column 4, curriculum value is significant if the STEM share is omitted.*

used in this report are sometimes highly correlated with student test scores, with values in the 0.18 (curriculum value) to 0.56 (student aid) range. They are also likely correlated with unobserved aspects of student ability, motivation, and ambition to earn a higher salary. Even with these correlations, it is somewhat reassuring that the economics literature consistently finds that the selectivity of a school predicts better student outcomes, across a variety of methods.[63]

Another potential weakness of the approach used here is that it requires that the quality measures are valid. This assumption is partly confirmed by the regression analysis itself, but the limitations of that analysis cannot rule out the possibility of omitted variables bias (or selection on unobservables). The LinkedIn alumni skills measure is particularly vulnerable to selection on unobservables, given that the skills could have been acquired outside of the college education. This bias may be partly mitigated by the fact that only the 25 most common skills for each college are used (because that is what

Appendix Table 5. Regression of Student and School Characteristics on Alumni Economic Outcomes, Omitting Observable Quality Measures

	Ln mid-career earnings	Occupational earnings power	Default rate	Default rate	Ln mid-career earnings, all graduates
Local price index 2012	0.00258***	-0.000313**	-0.0744***	-0.0851***	0.00146**
	(0.000494)	(0.000132)	(0.0144)	(0.0138)	(0.000571)
Modal degree level is two year	0.00632	-0.0101**	-0.141	0.113	
	(0.0284)	(0.00486)	(0.560)	(0.407)	
Modal degree level is bachelor's	0.125*	-0.0213***	0.229	-0.148	-0.00912
	(0.0649)	(0.00748)	(0.812)	(0.642)	(0.0178)
Modal degree level is master's	0.137**	-0.0222***	0.424	-0.0582	
	(0.0667)	(0.00840)	(0.904)	(0.753)	
Modal degree level is doctorate or professional		0.0355**	-2.468	-1.292	
		(0.0160)	(1.724)	(1.323)	
Online only enrollment	-0.0832*	-0.0114	-1.071	-0.179	-0.115**
	(0.0500)	(0.0119)	(1.330)	(1.301)	(0.0519)
Percent of students enrolled part time	0.0729**	-0.00650	1.349*	-0.186	0.0915**
	(0.0339)	(0.00690)	(0.789)	(0.476)	(0.0394)
Percent of freshman from same state	-0.0397*	0.00376	-1.521***	1.254**	-0.0512**
	(0.0213)	(0.00496)	(0.556)	(0.498)	(0.0242)
Foreign-born student share of enrollment	-0.0335	0.150***	-1.664	-1.066	-0.0463
	(0.0897)	(0.0204)	(2.420)	(2.252)	(0.0982)
Asian student share of enrollment	0.360***	0.0593***	-7.921***	-9.380***	0.419***
	(0.0939)	(0.0227)	(2.457)	(2.112)	(0.113)
White student share of enrollment	0.00498	0.000395	-4.346***	-4.711***	-0.0833**
	(0.0276)	(0.00630)	(0.702)	(0.511)	(0.0348)
Average age of students	-0.0115***	0.00118***	0.137***	0.168***	-0.0118***
	(0.00179)	(0.000377)	(0.0427)	(0.0277)	(0.00210)
Female share of students	-0.392***	-0.114***	-8.599***	-6.950***	-0.412***
	(0.0348)	(0.00740)	(0.808)	(0.479)	(0.0399)
Percent of students receiving no aid	-0.000650*	3.51e-05	0.0231**	0.0323***	-0.000796*
	(0.000354)	(8.29e-05)	(0.00947)	(0.00802)	(0.000461)
Ln Pell grant aid per student	-0.0556***	0.00850***	2.284***	1.797***	-0.0994***
	(0.0135)	(0.00314)	(0.364)	(0.286)	(0.0173)

LinkedIn publishes), which suggests that the school is playing an important role in at least preparing students to acquire these skills.

How to treat observable quality in the value-added calculation

Another issue is whether Q variables should be omitted entirely when calculating value-added. We believe this would not work, as argued above. Specifically, omitting Q would exaggerate the effects of student characteristics within the model. This can be seen in comparing the results of Appendix Table 4 to those of Appendix Table 5, which omits observable quality measures.

Using salary outcomes, the F-test for the student variables (percent of students receiving federal loans, percent of freshman from in-state, average age, percent women, percent no aid, average Pell grant size per student, test scores and its squared term, and racial-ethnic percentages) is dramatically higher when Q variables are omitted (55) compared to when they are included (18). Indeed, across the five models, the F-statistics on student characteristics are two to three times as high as in the models omitting Q.

Appendix Table 5 (cont.). Regression of Student and School Characteristics on Alumni Economic Outcomes, Omitting Observable Quality Measures

	Ln mid-career earnings	Occupational earnings power	Default rate	Default rate	Ln mid-career earnings, all graduates
Percent of students receiving federal loans	-0.000511**	6.80e-05	-0.00394	-0.0293***	-0.000630*
	(0.000253)	(5.58e-05)	(0.00650)	(0.00553)	(0.000337)
LinkedIn salary bias	-0.0172	0.00551*	1.229***		0.0165
	(0.0153)	(0.00320)	(0.380)		(0.0191)
Imputed standardized math scores (standardized)	0.0225**	0.0165***	-1.840***	-2.059***	0.0311***
	(0.00930)	(0.00254)	(0.276)	(0.278)	(0.0102)
Imputed standardized math scores (standardized)^2	0.0205***	0.00604***	0.108	-0.0365	0.0125***
	(0.00294)	(0.000756)	(0.0825)	(0.0822)	(0.00363)
Constant	11.85***	11.18***	1.965	7.223	12.29***
	(0.170)	(0.0460)	(5.025)	(6.705)	(0.202)
F-statistic on state fixed effects	2.1	2.1	5.8	4.8	2.7
F-statistic on student effects	54.9	71.3	65	115.5	51.3
F-statistic on graduate shares by degree level	1.8	7.8	10.9	10.2	1.6
F-statistic on Carnegie classifications	3	3.9	4.6	7.4	3
Observations	1,172	2,045	1,936	5,420	866
Adjusted R-squared	0.811	0.592	0.789	0.525	0.725

*Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. All regressions include control variables for the basic Carnegie classification categories, state fixed effects, and percentage of graduates from each degree level. F-statistics shown above.*

Since Q and student characteristics are correlated, omitting Q diminishes the correlation between Q and any final value-added metric. Appendix Table 6 shows the correlations between the alternative value-added metrics and student characteristics (the top two rows) and Q variables. The value-added measure derived from omitting Q entirely has almost no correlation with either student characteristics or measurable quality variables. By contrast, the value-added measure derived from ϵ above (where Q is included only to calculate coefficients, but omitted when calculating the error based on those coefficients) is highly correlated with the quality measures and has some correlation with test scores and student characteristics. This strikes us as more accurate, since observable measures of quality—like the graduation rate—should be correlated with value-added (indeed, we show they are in Appendix Table 4). It is also more realistic. It would be strange if the most selective schools like Harvard and Swarthmore were unable to recruit and retain good teachers or otherwise provide valuable learning experiences to their students.

Appendix Table 6. Correlations Between Value-Added Calculations Under Different Methods and Student and Quality Measures				
	Value-added omits Q entirely		Value-added assigns average Q	
	Salary	Repayment rate	Salary	Repayment rate
Ln of Pell aid per student	-0.03	-0.07	-0.31	-0.25
Imputed test scores	0.03	0.04	0.55	0.45
Ln of average student aid	0.08	0.06	0.48	0.47
Average salary of instructional staff	0.09	0.04	0.47	0.29
Ln of alumni skills	0.14	0.08	0.56	0.37
Percentage of students graduating in STEM field	0.16	0.06	0.27	0.02
Ln curriculum value	0.17	0.10	0.55	0.31
Graduation rate	0.03	0.13	0.52	0.59

Others may have preferred a model that included Q but calculated value-added with respect to only unobservable quality. This would be μ from equation 2, and it would understate value-added by a large amount, because it would not allow any of the measured quality variables to contribute. We do plan on making μ available to the public because we think it provides an interesting interpretation: We consider it the unmeasured aspects of value-added, such as teacher or administrative excellence. It is small for schools like MIT, whose value-added is largely explained by alumni skills and the curriculum, but high for some liberal arts colleges whose graduates earn high salaries despite majoring in less lucrative fields. We refer to this as the college's "x-factor."

7. Empirical comparison with popular rankings

Appendix Tables 7 and 8 show the results of regressing various rankings on rankings for the two major outcomes (earnings and student loan default rates), while controlling for student and school characteristics. The results from these regressions are shown in Figures 10 and 11 of the report.

These regressions repeat the analysis summarized in equation 2 but replace the quality (Q) variables with one summary measure of quality: the popular rankings from *Money*, *Forbes*, and *U.S. News*, and the value-added measure produced for this report. The outcome variables are also ranked to ease interpretation. Rankings are structured such that the highest value-added score (or best measure) ranks the school number one. It is expected, therefore, that rankings would be positively correlated with rank for earnings and default rates (where a rank of one signifies the lowest default rate), which is borne out in the analysis.

Money and *Forbes* make their rankings available by school in a fairly accessible way, which facilitated comparisons.[64] *U.S. News*, however, distinguishes national universities from liberal arts colleges, regional universities, and regional colleges. The regional group is deemed to be of lower rank, so instead of misattributing high quality to high-ranking schools on those measures, the regional groups were simply omitted from the analysis. To avoid comparing different schools, these regressions include only the 196 colleges with rankings across all three major sources for the salary regressions and the 212 colleges that meet those criteria with default rate data.

As explained in the body of the report, the value-added rankings substantially outperform the conventional rankings. The coefficients and t-statistics are much larger using the value-added measure. In other words, a change in rank on value-added is worth more in terms of explaining student outcomes.

To save space we do not report results from other regressions of interest, but summarize the results here.

The same analysis for occupational earnings power outcomes generates a coefficient on the value-added rank of 0.32 and is highly significant. None of the conventional rankings are significant and none have coefficients above 0.17.

As mentioned above, the value-added coverage with respect to default rates can be expanded from 1,700 to over 4,400 by dropping teacher salaries, alumni skills, and the LinkedIn bias variable. When used in the same regression form as in Appendix Table 8, the adjusted R-squared of the model falls slightly, but the resulting value-added metric still dramatically outperforms the popular rankings. The coefficient on the broadest value-added metric is 0.33, only slightly lower than the more robust measure, and highly significant (t-stat equals 17). Moreover, when included in the same regression as the three popular rankings, only the broad value-added measure is significant and highly so.

We also test the predictive power of the model's unmeasured aspects of quality: the "x factor," represented by Đ. It turns out that the coefficient on Đ is 0.23 for the salary ranking model, 0.26 with respect to default rate rankings, and 0.21 for occupational earnings power. In all, these coefficients are higher than the conventional final rankings.

To summarize, the value-added method is demonstrably more effective at predicting student outcomes given known institutional and student characteristics. Even the x-factor generated from this analysis is more informative than the conventional rankings.

Checking for nonlinear effects of college ranking on outcome rankings

The assumption behind the above exercise is that there is a linear relationship between school rank and outcomes and that the slope is consistent within each of the four ranking systems as the rank increases. To relax this assumption, we perform a simple regression of salary rank on college rank, while controlling for test scores and the log of Pell grant aid (to roughly adjust for student incomes at admission), but instead of using the entire sample of colleges with rankings for each system, we report the results separately by quartile for each ranking system.

For student earnings, Appendix Table 9 reports the results. The coefficient on the Brookings value-added measure is consistently large across quartiles, ranging from 0.26 to 0.40. This means that a one-unit improvement in the value-added rank predicts between a 0.26 and 0.40 improvement in salary rank. The T-statistic is also consistently high (2.3 is the lowest) and as high as 23 for the entire sample. For the conventional rankings, the coefficients are much smaller, not consistent, and insignificant within each quartile. This is evidence that at any point in the ranking (meaning near the top, middle, or bottom), the Brookings value-added measure outperforms conventional rankings in terms of predicting salary outcomes conditional on rough measures of student characteristics.

We conducted the same exercise for student default rates. There the evidence was also clear. With the exception of the second quartile, the Brookings value-added rank always has higher t-statistics than the alternatives and a higher coefficient in all but one other case. *U.S. News* and *Forbes* do considerably better at predicting default rates than they do at predicting earnings, conditional on Pell awards and test scores, and yet, at the third quartile, a higher (better) rank on both *Forbes* and *U.S. News* predicts higher defaults.

As a further robustness check, we consider that the Brookings measures are estimated on a much larger sample of schools (1,785 colleges), whereas only 212 could be compared here. (This was less of an issue with the PayScale salary calculation, which was done for 1,139 colleges). Thus, the coefficients and error terms calculated for the value-added metric were done with many out-of-sample colleges. The last column of Appendix Table 10 shows the results when value-added is recalculated using only the sample of 212 colleges with rankings across each system. The t-statistic falls almost in half but the coefficient becomes much larger. The second and third quartiles become far more accurate, whereas some accuracy is lost in the top and bottom quartiles. The results were also recalculated for the fully specified Appendix Table 8 regression. The coefficient on the Brookings value-added rank for default rate rank was 0.50 and highly significant.

To summarize, these results support the main findings from Appendix Tables 7 and 8 that the value-added measure predicts student outcomes with greater precision than conventional measures. Those results do not appear to be driven by only one small part of the distribution or other nonlinear dynamics.

Appendix Table 7. Regression of Rank, Student, and School Characteristics on Rank of Mid-Career Earnings

	Rank of mid-career earnings			
	1	2	3	4
Money rank	0.0855***			
	(0.0241)			
Forbes rank		0.0151		
		(0.0512)		
U.S. News rank			-0.158	
			(0.176)	
Value-added rank				0.350***
				(0.0117)
Local price index 2012	-0.140	-0.182	-0.117	-0.869***
	(0.431)	(0.453)	(0.457)	(0.157)
Modal degree is bachelor's		2.647		6.230
		(12.59)		(4.297)
Modal degree is master's	1.174		-5.344	
	(11.98)		(12.77)	
Percent of students enrolled part time	82.43	103.9	121.1*	-29.08
	(68.35)	(72.68)	(72.77)	(24.91)
Percent of freshman from same state	22.21	6.012	12.27	6.779
	(21.39)	(22.28)	(22.74)	(7.548)
Foreign-born student share of enrollment	5.666	-18.32	-0.446	84.88***
	(68.96)	(72.90)	(73.93)	(24.98)
Asian student share of enrollment	-214.2***	-259.6***	-262.0***	-76.98***
	(69.58)	(72.14)	(71.89)	(25.40)
White student share of enrollment	-12.85	-26.47	-19.53	15.53
	(38.17)	(40.71)	(40.21)	(13.77)
Average age of students	-4.853	-6.728	-6.348	4.761***
	(4.209)	(4.397)	(4.394)	(1.553)
Female share of students	242.2***	283.5***	281.6***	103.4***
	(32.11)	(31.46)	(31.44)	(12.36)
Percent of students receiving no aid	0.187	0.0942	0.0599	-0.245**
	(0.279)	(0.292)	(0.293)	(0.101)
Ln Pell grant aid per student	23.52*	22.99	25.09*	23.94***
	(13.38)	(14.50)	(14.07)	(4.818)
Percent of students receiving federal student loans	0.322	0.714**	0.828**	0.224**
	(0.325)	(0.330)	(0.332)	(0.110)
LinkedIn salary bias	0.601	0.334	0.312	5.679
	(15.84)	(16.65)	(16.60)	(5.707)
Imputed standardized math scores (standardized)	-19.21	-23.40	-34.97**	-5.323
	(12.61)	(16.66)	(16.11)	(4.539)
Imputed standardized math scores (standardized)^2	2.676	2.893	5.208	-1.380
	(3.516)	(4.536)	(4.049)	(1.274)
Constant	-70.69	-24.17	-48.43	-187.4***
	(144.0)	(154.1)	(141.7)	(52.31)
Observations	196	196	196	196
Adjusted R-squared	0.747	0.721	0.722	0.967

*Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All regressions include controls for Carnegie classification and percentage of graduates by award type.*

Appendix Table 8. Regression of Rank, Student, and School Characteristics on Rank of Default Rate

	Rank of default rate on federal student loans			
	1	2	3	4
Money rank	0.0697***			
	(0.0248)			
Forbes rank		0.208***		
		(0.0499)		
U.S. News rank			0.186	
			(0.191)	
Value-added rank				0.416***
				(0.0245)
Local price index 2012	-0.151	-0.189	-0.257	-1.951***
	(0.496)	(0.480)	(0.514)	(0.306)
Modal degree is bachelor's	10.32	7.890		16.32**
	(14.01)	(13.59)		(8.104)
Modal degree is master's			-10.14	
			(14.68)	
Percent of students enrolled part time	-2.000	-36.06	-8.137	-24.83
	(80.08)	(78.21)	(83.80)	(46.43)
Percent of freshman from same state	16.72	-2.844	2.834	-1.375
	(23.48)	(22.66)	(24.34)	(13.50)
Foreign-born student share of enrollment	177.2**	124.3	137.2	83.33*
	(79.81)	(77.32)	(83.70)	(46.27)
Asian student share of enrollment	-134.8*	-186.6**	-165.4**	-196.5***
	(81.12)	(77.74)	(82.33)	(46.51)
White student share of enrollment	4.301	-42.07	-19.91	-20.14
	(41.98)	(40.75)	(43.01)	(24.06)
Average age of students	1.713	-0.720	0.200	3.250
	(4.865)	(4.711)	(5.002)	(2.818)
Female share of students	-40.17	-7.024	-5.999	-142.9***
	(36.90)	(34.08)	(36.20)	(21.88)
Percent of students receiving no aid	0.569*	0.484	0.471	0.213
	(0.321)	(0.307)	(0.327)	(0.184)
Ln Pell grant aid per student	41.13***	26.76*	37.89**	62.18***
	(15.06)	(14.88)	(15.49)	(8.829)
Percent of students receiving federal student loans	-0.382	-0.367	-0.161	0.127
	(0.351)	(0.331)	(0.354)	(0.194)
LinkedIn salary bias	-12.18	-9.239	-9.440	-1.592
	(18.10)	(17.50)	(18.53)	(10.49)
Imputed standardized math scores (standardized)	-38.22***	-0.843	-31.88*	6.731
	(13.64)	(16.43)	(17.25)	(8.379)
Imputed standardized math scores (standardized)^2	1.700	-8.097*	0.0886	-0.936
	(3.844)	(4.415)	(4.304)	(2.235)
Constant	-10.50	70.18	-53.54	-131.8
	(157.7)	(153.5)	(171.6)	(91.78)
Observations	212	212	212	212
Adjusted R-squared	0.690	0.709	0.674	0.896

*Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All regressions include controls for Carnegie classification and percentage of graduates by award type.*

Appendix Table 9. Coefficient and T-Statistic on College Ranking by Quartile From Regression of College Ranking on Salary Rank, Controlling for Test Score and Pell Grant Aid

	Money	*Forbes*	*U.S. News*	Value-added
All colleges	0.10	0.08	-0.07	0.36
	5.32	2.28	-0.56	22.86
Top quartile ranking	0.22	0.18	-0.30	0.38
	1.30	0.58	-0.46	3.92
Second quartile ranking	0.19	-0.24	1.01	0.40
	1.12	-0.78	1.54	3.36
Third quartile ranking	0.18	0.10	-0.46	0.26
	1.06	0.56	-1.07	2.31
Fourth quartile ranking	0.06	0.03	0.10	0.38
	0.96	0.37	0.33	4.83

Note: T-statistics below coefficients. Ranking for salary is regressed on school rankings, controlling for test scores and log of Pell grant aid.

Appendix Table 10. Coefficient and T-Statistic on College Ranking by Quartile From Regression of College Ranking on Default Rate Rank, Controlling for Test Score and Pell Grant Aid

	Money	*Forbes*	*U.S. News*	Value-added	Value-added, same sample
All colleges	0.00	0.16	0.34	0.32	0.47
	0.14	5.20	2.72	14.67	7.51
Top quartile ranking	0.36	0.22	0.08	0.97	0.29
	1.55	0.88	0.15	4.52	0.71
Second quartile ranking	0.40	0.32	0.71	0.13	0.91
	1.76	1.15	1.14	0.83	2.43
Third quartile ranking	0.03	-0.01	-0.55	0.17	1.09
	0.21	-0.05	-1.15	1.21	2.56
Fourth quartile ranking	-0.06	0.15	0.52	0.27	0.39
	-0.91	2.44	1.99	3.30	1.34

Note: T-statistics below coefficients. Ranking for default rate (one indicating lowest rate) is regressed on school rankings, controlling for test scores and log of Pell grant aid. The last column calculates value-added using only the colleges with rankings across each system.

Endnotes

1. Brad Hershbein and Melissa Kearney, "Major Decisions: What Graduates Earn Over Their Lifetimes" (Washington: Hamilton Project, 2014).

2. Jaison R. Abel, Richard Deitz, and Yaqin Su, "Are Recent College Graduates Finding Good Jobs?" *Current Issues in Economic and Finance* (Federal Reserve Bank of New York), 20 (1) (2014); Jonathan Rothwell, "Still Searching: Job Vacancies and STEM Skills" (Washington: Brookings Institution, 2014).

3. Richard Vedder, Christopher Denhart, and Jonathan Robe, "Why Are Recent College Graduates Underemployed? University Enrollments and Labor Market Realities" (Washington: Center for College Affordability and Productivity, 2013).

4. Christopher Avery and Sarah Turner, "Student Loans: Do College Students Borrow Too Much—Or Not Enough?" *Journal of Economic Perspectives* 26 (1) (2012): 165–92; Hershbein and Kearney, "Major Decisions."

5. Among 2014 ACT test takers—about 57 percent of all graduating high school students—just 26 percent scored high enough to be considered ready for college in all four core subjects (English, reading, math, and science). Readiness is defined as having at least a 50 percent probability of earning a B in a college course or a 75 percent probability of earning at least a C. Readiness in math and science was particularly low compared to English and reading. (ACT, "The Condition of College and Career Readiness 2014," available at **http://www.act.org/research/policymakers/cccr14/readiness.html**.) Likewise, despite massive labor market demand for computer science knowledge, high school preparation for success in that field is also extremely limited. Only 1 percent of Advanced Placement exam test takers—just 22,273 students—took an AP computer science exam in high school in 2013 and, of those, only 11,040 scored a 4 or 5, the result which indicates that the test taker is well qualified to receive college credit. See College Board, "10th Annual AP Report to the Nation," available at **http://apreport.collegeboard.org/**.

6. Scott A. Ginder and Janice E. Kelly-Reid, "Enrollment in Postsecondary Institutions, Fall 2012; Financial Statistics, Fiscal Year 2012; Graduation Rates, Selected Cohorts, 2004–09; and Employees in Postsecondary Institutions, Fall 2012" (Washington: U.S. Department of Education, 2013). On average 13 percent of students complete their degree within six years at a different school than the one first attended; D. Shapiro et al., "Completing College: A National View of Student Attainment Rates—Fall 2008 Cohort," (Herndon, Va.: National Student Clearinghouse Research Center, 2014).

7. John Bound, Michael F. Lovenheim, and Sarah Turner, "Why Have College Completion Rates Declined? An Analysis of Changing Student Preparation and Collegiate Resources," *American Economic Journal: Applied Economics* 2 (3) (2010): 129-57; Sarah R. Cohodes and Joshua S. Goodman, "Merit Aid, College Quality, and College Completion: Massachusetts' Adams Scholarship as an In-Kind Subsidy," *American Economic Journal: Applied Economics* 6 (4) (2014): 251–85; Susan Scrivener and Michael J. Weiss, "Two-Year Results From an Evaluation of Accelerated Study in Associate Programs (ASAP) for Developmental Education Students" (New York: MRDC, 2013); Lisa Barrow, Lashawn Richburg-Hayes, Cecilia Elena Rouse, and Thomas Brock, "Paying for Performance: The Education Impacts of a Community College Scholarship Program for Low-Income Adults" (Federal Reserve Bank of Chicago, 2010); Kenneth I. Maton et al., "Enhancing the Number of African Americans Who Pursue STEM PhDs: Meyerhoff Scholarship Program Outcomes, Processes, and Individual Predictors," *Journal of Women Minorities in Science and Engineering* 15 (1) (2009): 15–37; Kathy Stolle-McAllister, Mariano R. Sto. Domingo, and Amy Carrillo, "The Meyerhoff Way: How the Meyerhoff Scholarship Program Helps Black Students Succeed in the Sciences," *Journal of Science Education and Technology* 20 (1) (2011): 5–16; Becky Wai-Ling Packard, "Effective Outreach, Recruitment, and Mentoring Into STEM Pathways: Strengthening Partnerships With Community Colleges," prepared for the National Academy of Science meeting "Realizing the Potential of Community Colleges for STEM Attainment" (2011); Thomas Kane, "Evaluating the Impact of the D.C. Tuition Assistance Grant Program," NBER Working Paper 9703 (2004); Thomas J. Kane, "A Quasi-Experimental Estimate of the Impact of Financial Aid on College-Going," Working Paper 9703 (2003); Susan Dynarski, "Hope for Whom? Financial Aid for the Middle Class and Its Impact on College Attendance," *National Tax Journal* 53 (3) (2000): 629-61; Susan Dynarski and Judith Scott-Clayton, "Financial Aid Policy: Lessons From Research," *Future of Children* 22 (1) (2013): 67-91.

8. William Bowen, Matthew Chingos, and Michael McPherson, *Crossing the Finish Line: Completing College at America's Public Universities* (Princeton, N.J.: Princeton University Press, 2009).

9. Caroline Hoxby and Christopher Avery, "The Missing 'One-Offs': The Hidden Supply of High-Achieving,

Low-Income Students," (Washington: Brookings Papers on Economic Activity, 2013).

10. Mai Seki, "Heterogeneous Returns to U.S. College Selectivity and the Value of Graduate Degree Attainment," Bank of Canada Working Paper (2013); Mark Hoekstra, "The Effect of Attending the Flagship State University on Earnings: A Discontinuity-Based Approach," *Review of Economics and Statistics* 91 (4) (2009): 717–24; Dan A. Black and Jeffrey A. Smith, "Estimating the Returns to College Quality With Multiple Proxies for Quality," *Journal of Labor Economics* 24 (3) (2006): 701–28; Mark Long, "College Quality and Early Adult Outcomes," *Economics of Education Review* 27 (5) (2008): 588–602; Mark Long, "Changes in the Returns to Education and College Quality," *Economics of Education Review* 29 (3) (2009): 338–47.

11. Stacy Berg Dale and Alan B. Krueger, "Estimating the Payoff to Attending a More Selective College: An Application of Selection on Observables and Unobservables," *Quarterly Journal of Economics*, 117 (4) (2002): 1491–1527; Stacy B. Dale and Alan B. Krueger, "Estimating the Effects of College Characteristics Over the Career Using Administrative Earnings Data," *Journal of Human Resources* 49 (2) (2014): 323-58.

12. Ibid.

13. David J. Deming, Noam Yuchtman, Amira Abulafi, Claudia Goldin, and Lawrence F. Katz, "The Value of Postsecondary Credentials in the Labor Market: An Experimental Study" (Cambridge, Mass.: NBER Working Paper 20528, 2014).

14. Peter Arcidiacono, "Ability Sorting and the Returns to College Major," *Journal of Econometrics* 121 (1–2) (2004): 343–75; Hershbein and Kearney, "Major Decisions."

15. One experiment finds that providing better information about graduation rates and costs causes high-achieving low-income students to increase their enrollment at selective colleges, where they will be expected to do better; Caroline Hoxby and Sarah Turner, "Informing Students About Their College Options: A Proposal for Broadening the Expanding College Opportunities Project" (Washington: Hamilton Project, 2013).

16. In this framework, it makes no difference if "quality" is observed or not in calculating value-added. In practice, however, it is important because predictions of student outcomes based on student and college characteristics will not be accurate if quality is ignored. To implement this, student outcomes are first estimated with quality included. That insures the relationship between student characteristics and outcomes is calibrated appropriately. Then, predicted outcomes are calculated as if quality was unknown and each school was exactly average on each measure of quality. The difference between the alumni's actual outcome and this predicted outcome represents value-added, which is itself composed of the measured and unmeasured aspects of quality.

17. As it happens, the PayScale-reported median earnings of graduates is higher than the average metropolitan area salary for occupations that typically require a high school diploma for every school, but a far more sophisticated analysis would be required to calculate the comparable non-attendee wage group.

18. Jesse M. Cunha and Trey Miller, "Measuring Value-Added in Higher Education: Possibilities and Limitations in the Use of Administrative Data," *Economics of Education Review* (42) (2014): 64-77.

19. Robert Kelchen and Douglas N. Harris, "Can 'Value Added' Methods Improve the Measurement of College Performance? Empirical Analyses and Policy Implications" (Washington: HCM Strategists, 2012).

20. For a small number of colleges (39), PayScale either reports data for both two-year and four-year graduates separately or for only one group when the other degree awarded is more commonly granted at the college. These observations were dropped because, for some schools, it would have resulted in two different earnings measures and for others it would have assigned earnings to an unrepresentative group of alumni.

21. The econometric models were also estimated using all alumni, whether or not they earned a higher degree after graduation at all or at a different college. The results were broadly similar, but the model with all alumni earnings was less precisely estimated. These data are not available from PayScale for community colleges.

22. U.S. Department of Education, "Three-Year Official Cohort Default Rates for Schools," available at **http://www2.ed.gov/offices/OSFAP/defaultmanagement/cdr.html**.

23. Military occupations are not covered in the BLS occupational survey, so data from the 2013 American Community Survey were used instead, based on micro-data made available from IPUMS.

24. For example, average SAT and ACT scores are higher for out-of-state University of Texas at Austin students than

for in-state students. See **http://bealonghorn.utexas.edu/whyut/profile/outofstate** (accessed March 2015).

25. Xianglei Chen, "Part-Time Undergraduates in Postsecondary Education: 2003–04" (Washington D.C.: U.S. Department of Education, National Center for Education Statistics, 2007).

26. The military academies provide tuition and living expenses to all students. Unfortunately, this means that no information is publicly available as to the income of entering students, meaning value-added measures could not be provided. However, many of the quality measures are available for these colleges.

27. Overall, the LinkedIn profiles are biased in that they are more likely to reflect higher-earning majors. To determine this, earnings by two-digit Classifications of Instruction Programs (CIP) code major were calculated from 2012 ACS for bachelor's degree earners in the labor force age 25 to 64. Then these salary values were imputed to each institution based on the mix of majors represented on LinkedIn and the actual mix of majors available on IPEDS. The average LinkedIn profile holder is in a field that earns, on average, 8 percent more per year. Since the ratio varies by college, this variable is used to control for the college's social media bias when predicting outcomes. The appendix shows which majors are most and least represented on LinkedIn relative to recent graduates.

28. Steven Ruggles, J. Trent Alexander, Katie Genadek, Ronald Goeken, Matthew B. Schroeder, and Matthew Sobek, Integrated Public Use Microdata Series: Version 5.0 [Machine-readable database]. (Minneapolis: University of Minnesota, 2010).

29. Although the census earnings data come from only bachelor's degree holders, the final value is applied to associate's degree programs as well, as explained in the appendix. Of associate degree graduates, 97.5 percent studied in degree fields (CIPs) that could be matched with census earnings in the same field for bachelor's degree holders.

30. PayScale has a sample size of 1.4 million U.S. degree holders, at time of writing, and they report an average sample size per school of 325 profiles. That total number is about 1.5 percent of the U.S. population with an associate's degree or higher, based on U.S. Census Bureau data. This sample size is slightly larger than the Census Bureau's ACS, but unlike that survey, PayScale's is not a random sample, since only those who visit the website and want a salary report enter their information

31. The CIP field-of-study codes do not distinguish between the level of the degree, so many bachelor's degrees field-of-study codes line up with associate's degree field-of-study codes. This is how bachelor's degree earnings by field were imputed to associate's degree holders. The real correlations might be even higher between ACS and PayScale earnings, but many of the field-of-study categories could not be precisely matched at both the bachelor's and associate's degree levels.

32. Correlation coefficients have a value between 0 and 1, with values closer to 1 indicating a stronger relationship between two variables. At a value of 1, a correlation coefficient between two variables indicates that an increase in one variable will be accompanied by an increase of the same magnitude in the other. A negative correlation coefficient indicates an inverse relationship between two variables.

33. Thomas Lemieux, "The 'Mincer Equation' Thirty Years After Schooling, Experience, and Earnings," in Shoshana Grossbard, ed., *Jacob Mincer: A Pioneer of Modern Labor Economics* (New York: Springer US, 2006) , Chapter 11.

34. Organization for Economic Cooperation and Development, OECD Skills Outlook 2013: First Results From the Survey of Adult Skills (Paris: OECD Publishing, 2013), available at **http://dx.doi.org/10.1787/9789264204256-en**; Peter Arcidiacono, "Ability Sorting and the Returns to College Major," *Journal of Econometrics* 121 (1–2) (2004): 343–75; Eric A. Hanushek, Guido Schwerdt, Simon Wiederhold, and Ludger Woessmann," Returns to Skills Around the World: Evidence From PIAAC, " forthcoming in *European Economic Review* (2014); Eric A. Hanushek, Gregory K. Ingram, and Daphne A. Kenyon, "Is Location Fate? Distributional Aspects of Schooling," in Education, Land, and Location (Cambridge, Mass.: Lincoln Institute of Land Policy, 2014).

35. Carnegie Classification, available at **http://classifications.carnegiefoundation.org/** (accessed December 2014). The website will soon be moved to Indiana University's Center for Postsecondary Research.

36. Sandy Baum and Patricia Steele, "Who Borrows Most? Bachelor's Degree Recipients With High Levels of Student Debt" (New York: College Board, 2010).

37. Tiffany Julian, "Work-Life Earnings by Field of Degree and Occupation for People With a Bachelor's Degree: 2011," American Community Survey Briefs (Census Bureau, 2012); Economics and Statistics Administration, "STEM: Good Jobs Now and for the Future" (U.S.

Department of Commerce, 2011); Anthony P. Carnevale, Nicole Smith, and Michelle Melton, "STEM: Science, Engineering, Technology, and Mathematics" (Washington: Georgetown University Center for Education and the Workforce, 2011); Todd Gabe, "Knowledge and Earnings," *Journal of Regional Science* 49 (3) (2009): 439–57; Paolo Buonanno and Dario Pozzoli, "Early Labor Market Returns to College Subject," *Labour* 23 (4) (2009): 559–88 ; Jin Hwa Jung and Kang-Shik Choi, "Technological Change and Returns to Education: The Implications for the S&E Labor Market," *Global Economic Review* 38 (2) (2009): 161–84; Arcidiacono, "Ability Sorting and the Returns to College Major"; Jonathan Rothwell, "Still Searching: Job Vacancies and STEM Skills" (Washington: Brookings Institution, 2014).

38. Analysis of unpublished data from Rothwell, "Still Searching."

39. Raj Chetty, John Friedman, and Jonah Rockoff, "Measuring the Impacts of Teachers I: Evaluating Bias in Teacher Value-Added Estimates," *American Economic Review* (104) (2014): 2593–632; Raj Chetty, John Friedman, and Jonah Rockoff, "Measuring the Impact of Teachers II: Teacher Value-Added and Student Outcomes in Adulthood," *American Economic Review* (104) (2014): 2633-79.

40. Lauren Chapman and Larry Ludlow, "Can Downsizing College Class Sizes Augment Student Outcomes? An Investigation of the Effects of Class Size on Student Learning," *Journal of General Education* 59 (2) (2010): 101–23. Moreover, many large classes at public research universities have regular breakout sections with smaller classes led by graduate teaching assistants, so it's not clear how one would measure class size accurately.

41. *Los Angeles Times*, "Students Lose Out in University Numbers Game," *Editorial*, December 22, 2014.

42. That is to say the t-statistic for the Brookings value-added rank is seven times larger than the t-statistic on the *Money* rank.

43. As discussed in the appendix, these results are roughly the same using an even more basic model. Imagine that the only information available about a college is its average test scores, its average level of Pell grant aid, its rank in the popular publications, and its rank in the Brookings value-added measure for salary. The Brookings value-added measure provides a much more useful tool in predicting earnings than the popular rankings.

44. For this exercise, nine regression models were run, comparing our value-added to *Money*, then *Forbes*, then *U.S. News* separately for each of the three outcomes. Conditional on the popular rankings, our rank always predicted a significantly higher rank on the student outcomes. Conditional on our rankings, however, the conventional rankings predicted either a zero or significantly negative change in rank.

45. Restricting the sample to those colleges with *U.S. News* rankings (universities and liberal arts colleges), the correlations with our value-added measures are very similar as above for the larger sample: 0.53, 0.38, 0.58 for salary, occupational earnings power, and repayment rates, respectively.

46. Scrivener and Weiss, "Two-Year Results From an Evaluation of Accelerated Study in Associate Programs (ASAP) for Developmental Education Students"; Barrow, et al., "Paying for Performance"; Maton et al., "Enhancing the Number of African Americans Who Pursue STEM PhDs:"; McAllister, Sto. Domingo, and Carrillo, "The Meyerhoff Way"; Packard, "Effective Outreach, Recruitment, and Mentoring into STEM Pathways"; Kane, "Evaluating the Impact of the D.C. Tuition Assistance Grant Program"; Kane, "A Quasi-Experimental Estimate of the Impact of Financial Aid on College-Going"; Dynarski, "Hope for Whom?"; Dynarski and Scott-Clayton, "Financial Aid Policy."

47. Donna Linderman, "Significant Increases in Associate Degree Graduation Rates: Accelerated Study in Associate Programs (ASAP)" (New York: City University of New York, 2012), available at **http://cuny.edu/academics/programs/notable/asap/about/evaluation/ASAP-Key-Eval-Prog-Overview-0901712.pdf**.

48. Eric P. Bettinger and Bridget Terry Long "Addressing the Needs of Underprepared Students in Higher Education: Does College Remediation Work?" *Journal of Human Resources* 44 (3) (2009): 736-71; Eric P. Bettinger, Angela Boatman, and Bridget Terry Long, "Student Supports: Developmental Education and Other Academic Programs," *The Future of Children* 23 (1) (2013): 93-115.

49. Kevin Eagan et al., "The American Freshman: National Norms 2014" (Los Angeles: Cooperative Institutional Research Program at the Higher Education Research Institution at UCLA, 2015).

50. State University System of Florida, Board of Governors, "Performance Based Funding Model" (June 2014), available at **http://www.flbog.edu/about/budget/performance_funding.php**.

51. State of North Carolina, Governor Pat McCrory Proposes Higher Investment for High-Demand Occupations," press release, April 10, 2014, available at **http://www.governor.state.nc.us/newsroom/press-releases/20140410/governor-pat-mccrory-proposes-higher-investment-high-demand**; Pennsylvania Higher Education Assistance Agency, Pennsylvania Targeted Industry Program (June 2014), available at **http://www.pheaa.org/funding-opportunities/pa-tip/**.

52. Mark Muro et al., "America's Advanced Industries: What They Are, Where They Are, and Why They Matter" (Washington: Brookings Institution, 2015).

Endnotes Appendix

53. It is also likely less accurate for graduate degree programs, but the earnings data calculated here included graduate degree holders, even if earnings are assigned using bachelor's fields of study, mitigating error. For example, people who study medicine as an undergraduate are more likely to get medical degrees. The medical field of study will therefore contain earnings potential beyond the bachelor's level.

54. Jonathan Rothwell, "The Hidden STEM Economy" (Washington: Brookings Institution, 2013).

55. The crosswalk and more information are available at the Department of Education National Center for Education Statistics website, **http://nces.ed.gov/ipeds/cipcode/resources.aspx?y=55** (accessed March 2015).

56. Jonathan Rothwell, "Still Searching: Job Vacancies and STEM Skills" (Washington: Brookings Institution, 2014).

57. Prasanna Tambe, "Big Data Investment, Skills, and Firm Value," *Management Science* 60 (6) (2014): 1452-69.

58. Social Networking Fact Sheet, Pew Research, Internet Project, **http://www.pewinternet.org/fact-sheets/social-networking-fact-sheet/**.

59. "mi impute" is the newer version of this program.

60. It is worth noting that in the empirical models used below, test scores are modeled quadratically, as that yielded a better fit than a linear model. As a robustness check, a dummy variable for schools with imputed test score data was interacted with actual test scores. This interaction term was insignificant in predicting economic outcomes and so rejected from models reported here.

61. Edward L. Glaeser and Joshua D. Gottlieb, "The Wealth of Cities: Agglomeration Economies and Spatial Equilibrium in the United States," *Journal of Economic Literature* 47 (4) (2009): 983-1028.

62. We assume the error term is college specific but does not have a regional component, given our regional control for prices, which is meant to capture, broadly, how the regional economy affects earnings.

63. Stacy B. Dale and Alan B. Krueger, "Estimating the Effects of College Characteristics Over the Career Using Administrative Earnings Data," *Journal of Human Resources* 49 (2) (2014): 323-58; Seki, "Heterogeneous Returns to U.S. College Selectivity and the Value of Graduate Degree Attainment"; Hoekstra, "The Effect of Attending the Flagship State University on Earnings"; Black and Smith, "Estimating the Returns to College Quality With Multiple Proxies for Quality"; Long, "College Quality and Early Adult Outcomes"; Long, "Changes in the Returns to Education and College Quality."

64. The one problem is that these sources, including PayScale, do not include IPEDS unit identification numbers, so colleges must be matched by name, which is time consuming and can increases the probability of error. For this analysis, an effort was made to carefully check the names and locations of each school to assign the correct IPEDS ID number.

B

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