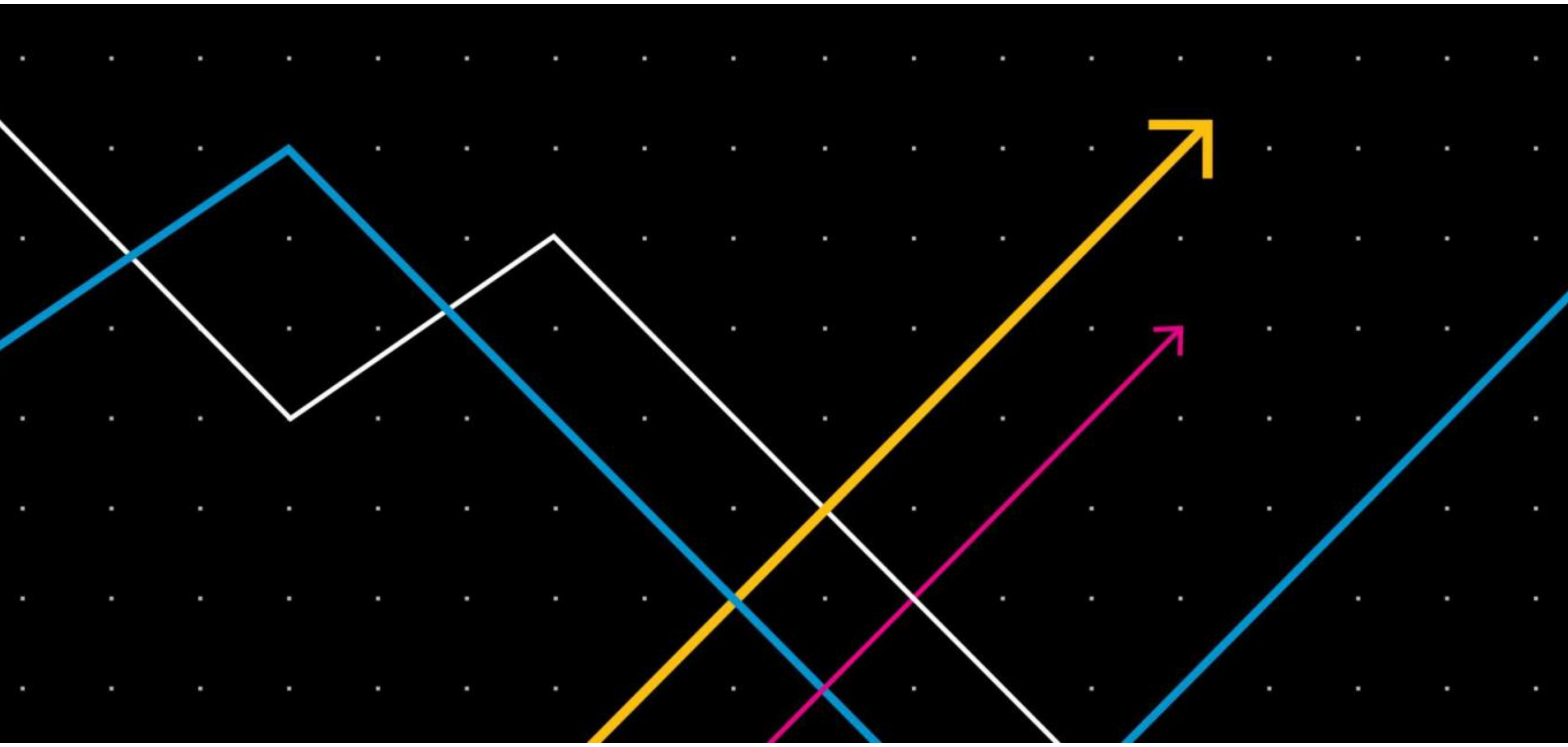

RESEARCH REPORT

Measuring Program-Level Completion Rates

A Demonstration of Metrics Using Virginia Higher Education Data

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Measuring Program-Level Completion Rates

Researchers and policymakers acknowledge that it is important to examine not only where a student enrolls in school but what she studies. Researchers have found that a student's major can have a large effect on long-run earnings and may influence earnings more than institutional selectivity. To help inform college decisionmaking, some states publish program-level earnings data, and the Trump administration has piloted the national development of these program-level earnings data. But program-level earnings data reflect only the earnings of students who graduated with the degree and may produce a biased estimate of what a typical student should expect. For example, if a program has a 25 percent graduation rate, a prospective student would have an expected value from enrolling in the program that is substantially lower than the published earnings data.

Program-level earnings data are best paired with information about a student's likelihood of success in a given major within the institution. Program-level graduation rates can provide this context, but there is no road map for developing a database of graduation rates. In this brief, we outline key criteria for a useful program-level graduation rate. This metric must include as many students as possible, provide an accurate and stable estimate of a student's likelihood of completion, be consistent across institutions, and align with institution-level graduation rates. We use data from Virginia to assess how close we can get to building the ideal metric and to evaluate the changes institutions would need to make to provide the most accurate measure of program completion.

The Importance of Program Completion Rates

Higher education policymakers have increasingly focused on understanding the effects of individual programs of study on a student's college and postcollege outcomes. The major a student selects can have a substantial effect on postgraduate earnings (Hershbein and Kearney 2014). In fact, the choice of a college major may influence earnings more than the selectivity of the student's institution (Carnevale et al. 2017; Eide, Hilmer, and Shawalter 2016).

Given these findings, some policymakers have pushed for the publication of program-level postgraduate earnings. Some states, including Colorado, Connecticut, Texas, and Virginia, already publish these data. The Trump administration is pushing the use of program-level earnings data nationally by including these data on the US Department of Education's College Scorecard.[1]

Despite enthusiasm for more program-level information, these data could mislead prospective students. Institution-level earnings data typically include any students who entered the institution in a given cohort year, regardless of whether they finished their degree. In contrast, program-level data provide information on the earnings of students who graduated with a given degree. This measure excludes students who did not graduate and may also conceal other institutional processes, such as differences in program requirements and standards. One concern is that a given program could have high postgraduate earnings by openly or inadvertently screening out students who might have otherwise enrolled in the major. Programs could screen out students through an application (e.g., for an honors program) or through difficult introductory courses. These within-institution screenings could artificially boost the earnings outcomes of program graduates, since they were selected from a broader pool of students at the institution.

Measuring the selection of students into (and out of) given majors and ensuing persistence within the major could also contribute to our understanding of earnings differences among different demographics of students. Female students typically earn less than male students who enrolled in the same institution (Flores 2016). Estimates of earnings differences by race or ethnicity are less clear. Broadly, the returns on a given level of education are constant across different subgroups (Barrow and Rouse 2006), but some researchers have observed differences in returns on bachelor's degrees among racial and ethnic groups that decrease when controlling for institution or major (McClough and Benedict 2017; Weinberger 1998).

A student's aptitude and ability for the subject matter may affect what major she selects or whether she switches majors, especially after she receives information about her aptitude through undergraduate course performance (Arcidiacono 2004; Turner and Bowen 1999). Yet even after controls for academic aptitude, differences in selected major by gender and by race or ethnicity persist (Dickson 2010). There is some evidence that women consider different factors than men when selecting or changing college majors; although interest in the subject is the most important factor for selecting a major, men are more likely to list compensation and job opportunities as a selection factor, while women are more likely to consider their aptitude in the field (Malgwi, Howe, and Burnaby 2010). Many studies look at the propensity of students to switch between a STEM major (science, technology, engineering, and mathematics) and a non-STEM major. Women and minorities are less likely to persist in STEM fields, and some of this difference may be explained by differences in academic preparation and educational experiences (Arcidiacono, Aucejo, and Spenner 2012; Griffith 2010). Further, the likelihood of completion varies by major. Students who switch into non-STEM majors are more likely to graduate on time than those who switch into STEM majors (Sklar 2014).

Producing data on program-level persistence, in the form of completion rates, could reveal differences in the effectiveness of different programs to retain low-income students, female students, or students of color. In addition to providing data for potential students and policymakers, these measures might highlight programs that have both strong outcomes and strong retention, providing models for other programs to adopt.

The Complexity of Program Completion Rates

Although within-institution completion rates could provide important context for policymakers and applicants as they decipher program-level earnings data, a standard measurement has not emerged. Measuring program-level graduation rates is complex because of wide variation in program size, program definition, time to completion, and the application or enrollment process.

The National Center for Education Statistics (NCES) has developed measurements of institution-level graduation rates. The NCES computes these statistics as part of provisions set out under the Student Right-to-Know and Campus Security Act, passed in 1990, which necessitated the development of completion or graduation rate data for all certificate- or degree-seeking full-time undergraduates. Institutions must calculate this rate to remain eligible for federal student financial aid programs, such as the Pell Grant Program and student loans. The NCES institution-level graduation metric focuses on completion at the starting institution for first-time full-time students within 150 percent of the normal time for their program (since 2008, the NCES has also calculated a completion rate at 200 percent of normal time). The NCES measure excludes from the cohort measurement students who have a severe disability, who die, who serve in the military, and who serve with a foreign aid service (e.g., the Peace Corps) or on an official church mission. Institution-level graduation rates are also available by student race or ethnicity, by gender, and by receipt of Pell grants and subsidized Stafford loans.

Another completion rate metric, the Student Achievement Measure, allows participating institutions to voluntarily track and report completion using National Student Clearinghouse data. The Student Achievement Measure allows for a more flexible completion measure, looking at part-time students as well as full-time students, and counting both those students who transferred to a different institution and those who graduated. Similar to the Integrated Postsecondary Education Data System measure, the Student Achievement Measure is available for subcohorts of students, such as those who received Pell grants, those who received veterans benefits, and students of color.

The variety of national institution-level graduation rate metrics—divided by part- and full-time status, student demographics, program completion time, and cohort exclusions—paint an important picture of institutional effectiveness. Policymakers and administrators need to understand how graduation rates differ within and between institutions by time allowed for completion, student financial need, gender, and race or ethnicity. But these metrics multiply further when measured not only at the institution level but at the program level.

For this assessment, we first focus on when program-level graduation rates should be measured and assessed. We then look at how we can ensure stability of the program-level measure, either by pooling cohorts of students or aggregating programs up into larger groups. Finally, we look at the type of metric we should produce—one that indicates the likelihood of graduation at all, given what program students select, or one that looks only at graduation from the given program.

Assessing Measurement Strengths and Weaknesses

A strong measure of program completion should include as many students as possible, provide an accurate and stable estimate of a student's likelihood of completion, be consistent across institutions, and align with institution-level graduation rates. Most importantly, these program-level rates should be intelligible to students who might enroll in the program. As a result, we evaluate multiple variations of simple measures, rather than use more complex regression-based measures.

We assess the validity of our measurements using a set of interconnected criteria, asserting that a strong measure should do the following:

- **Include as many students as possible.** Capturing students within a declared major is easier for students enrolled in two-year institutions than for those enrolled in four-year institutions. In four-year institutions, students may not declare a major until their second year or later. By moving the "major entry" point later in a student's enrollment, we may identify more students in a declared major, but we may also miss students who left the institution before declaring a major.
- **Provide an accurate and stable estimate of a student's likelihood of completion.** Small programs may have completion rates that are inconsistent over time. For example, a program

with a cohort of only four students could experience wide swings in graduation rates from year to year. If two students complete within six years, the graduation rate is 50 percent, but moving one more student across the finish line would bump the rate to 75 percent. One way to account for this concern is to pool majors of similar types, but this may mask variation within programs in the given pool. For example, when we begin to roll up categories of majors, we group mathematics and statistics together, military technology and applied sciences together, and science technologies and technicians together, even though student success in these fields may vary substantially, even within a single institution.

- **Be consistent across institutions.** We aim to develop a measure that could be used consistently across a state. The more our metric changes based on the institution, its students, and its programming, the less useful it is as a comparative tool.
- **Align with institution-level graduation rates.** One element of our measure's face validity is whether our program-level completion rates generally align with institution-level graduation rates. Our program-level graduation rates may vary within a given institution, but a weighted average should be representative of institution-level graduation rates for the cohort.
- **Be intelligible to those who might enroll in the program.** We may be able to more precisely derive the effects of enrollment in a given program within an institution on likelihood of completion using more sophisticated statistical techniques. But potential students and policymakers need measurements they can understand. Regression coefficients and similar measures could be confusing for a lay audience and do not mirror other data on graduation rates.

Data Used for Assessment

We use student-level data from the Virginia Longitudinal Data System, and we follow students who entered any public or private nonprofit postsecondary institution in Virginia as a freshman in the fall of 2008, 2009, 2010, or 2011. We obtain data for every student enrolled in a higher education program offering either baccalaureate or occupational and technical credit. These data follow students from their starting year through the spring of 2017, with semester-level information on institution enrollment, major, and degree progress.

Though these data are extensive, they are not comprehensive. It is difficult to ascertain whether and when a student is enrolled in a program full time or part time, which prevents us from developing separate benchmarks for college completion for these different types of students. Furthermore, though we can observe whether students are enrolled in an institution in a given semester and whether they receive a degree, the data do not specify whether students who are no longer enrolled have dropped out permanently or taken leave (though we can observe whether they reenroll within the data's time frame). Thus, although other measures of college completion often account for students who have left school because of military service, church missions, disability, or death, the structure of our data does not allow us to make similar adjustments.

Measurement of Program Completion Rates

With these limitations in mind, we construct measures of college completion for freshmen entering Virginia's public and private nonprofit institutions. Although we build multiple measures along several dimensions, we hold many elements of these measures constant. We measure graduation rates within six years of entry. For students who obtain multiple degrees from an institution, we use only their first degree for our measure. We look at completion within the institution where the student started as a freshman. Thus, if a student transfers schools without attaining a degree, we do not count her within the program graduation rate, even if she completed a degree at the other institution.

In these data, majors are defined by the Classification of Instructional Programs (CIP). Because these classifications are highly specific, we define three groupings that allow us to compare larger groups of students, especially across institutions (appendix tables A.1 and A.2). The first grouping uses the 47 broad CIP classifications (two-digit codes) that encompass the more specialized (six-digit) program codes. From this, we define a reduced set of 12 codes that combine similar areas of study. Finally, we assign each major code a designation of STEM or non-STEM. In addition to school and enrollment within a major, these data contain extensive information on each student's demographics, Virginia high school enrollment, and academic metrics (e.g., SAT scores and grade point averages).

We produce datasets that allow us to compare these graduation metrics between schools and majors generally, as well as programs within a school. We derive program-level completion rates based on declared student major at different points in time, including the fall of the first, second, and third year of enrollment. This is useful given that at some schools, particularly the University of Virginia and the College of William and Mary, a large proportion of students do not declare a major in the first two years.

We develop two types of program-level completion rates. First, we look at whether the student graduates with a degree in any field (conditional on declaring a major at a given point in time). Second, we look at whether students graduate with the same major or field they declared at the time of measurement. Both measures could provide value for students and policymakers, and the difference between these measures provides a rough sense of the attrition rate out of the program or field among students who complete another degree at the institution.

TABLE 1

Potential Measures of Program-Level Graduation Rates

Categorization of the major	Entry (fall semester) measurement	Graduation rate type
Two-digit CIP codes	First year (2- and 4-year schools)	Any degree
		Same degree
	Second year (2- and 4-year schools)	Any degree
		Same degree
	Third year (4-year schools only)	Any degree
		Same degree
12 categories of majors	First year (2- and 4-year schools)	Any degree
		Same degree
	Second year (2- and 4-year schools)	Any degree
		Same degree
	Third year (4-year schools only)	Any degree
		Same degree
STEM and non-STEM	First year (2- and 4-year schools)	Any degree
		Same degree
	Second year (2- and 4-year schools)	Any degree
		Same degree
	Third year (4-year schools only)	Any degree
		Same degree

Note: CIP = Classification of Instructional Programs; STEM = science, technology, engineering, and mathematics.

Table 1 provides an example of the measures we develop, given the three dimensions of measurement we outline above. Not including separate comparisons of two- and four-year schools, or the pooling of cohorts, we develop and assess 18 versions of program-level graduation rates. We assess how well these metrics stand up to the criteria we developed for identifying a strong metric. Notably, all 18 are straightforward, meeting our criterion that they could be easily explained to a student who was considering enrolling in one of these schools or a policymaker assessing differences between programs or institutions.

Assessing Program Completion Rates

Using questions aligned with our criteria for a strong program-level graduation rate metric, we evaluate these 18 metrics to find the strongest metric. We look at the validity of our simplification assumptions, how entry timing affects outcomes, the consistency of program-level metrics over time, and whether we should count any graduation (as opposed to graduation within a major) as the metric of choice.

How Valid Are Our Assumptions?

We simplify a few elements of our graduation rate to focus on the unique challenges of the measure—namely, the levels at which the measure is produced, the point at which the measure is taken, and the type of graduation (i.e., in any field or in the same field as the declaration metric). Our first assessment of these program completion measures is to validate that we are not oversimplifying our model.

SIMPLIFYING PROGRAM TYPES

We look at three levels of program definition: two-digit CIP code, a set of 12 general fields of study, and STEM versus non-STEM. For this analysis, we do not use the full six-digit CIP code, as these codes may not be used consistently by institutions for what are largely equivalent courses of study. For example, in 2013–14, one Virginia institution offered a major in speech communication and rhetoric (090101), another offered a major in mass communication and media studies (090102), and a third offered "communication and media studies, other" (090199). None of these institutions offered a major in either of the other two categories. Having the two-digit CIP code as our base set of categories allows us to compare majors that are similar across institutions. Further, if an institution decided to change the CIP classification of its communications major, we would still capture students as being in the same field.

One risk of this approach is that we fail to capture meaningful differences between specific undergraduate majors within a CIP code. This is a concern at institutions that have a high number of specific majors related to its mission. Virginia Commonwealth University School of the Arts, for example, has 14 majors under CIP code 50 (visual and performing arts). And Virginia Tech has 12 majors under CIP code 14 (engineering). But these cases are the exception. Sixty-seven percent of all institution-major pairs were the only major within a given two-digit CIP code (enrolling 44 percent of all students). And just 3 percent of institution-major pairs (enrolling 16 percent of all students) were placed in a two-digit CIP category with five or more other majors.

USING A STANDARD SIX-YEAR TERM

Across all our graduation rates, we allow students six years to graduate. We use this six-year term because it correlates to 150 percent of the time it would typically take a first-time full-time student to earn her bachelor's degree. For a two-year program, this means we assess completion at 300 percent of the time for first-time full-time students. But because students working toward an associate's degree may be more likely to stop out and return, move from part-time to full-time status (and vice versa), or take remedial or developmental classes, this longer period may be appropriate (Crosta 2014).

We cannot easily discern part- and full-time status in the data we have, and the national measurement of graduation rates for students who are not enrolled as first-time full-time students is still fairly new. But our six-year cutoff might obscure some information about those who graduated from the institution outside this window. To test this, we use our oldest cohort—students who entered higher education in 2008–09—and look for students who graduated from the same institution in 2015–16 or later (i.e., after the six-year cutoff). Ninety-six percent of students who we record as graduating from the same institution they enrolled in in 2008–09 graduated within six years. The share of students who graduated within this six-year period varies by school type: 97 percent of recorded graduates who were enrolled in four-year schools graduated with six years, while 91 percent of recorded graduates who were enrolled in two-year schools completed within six years.

Because our six-year time frame captures completion outcomes for nearly all students who enrolled at these institutions, it is unlikely that we are substantially biasing our overall estimates of program-level completion estimates by selecting this common window. But if some programs are more likely to enroll part-time students—who may graduate outside the six-year window—it is possible we may underestimate specific program-level graduation rates.

How Does Program Entry Affect Outcomes?

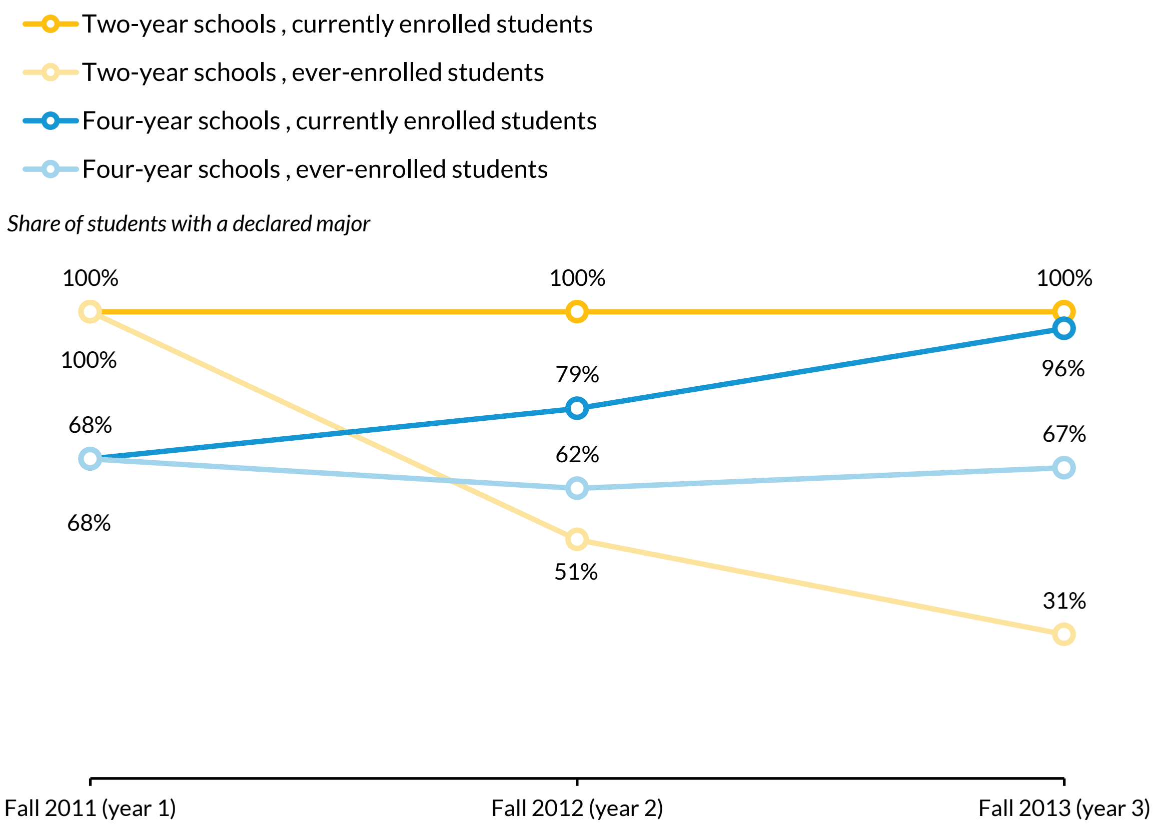
The point at which students are captured as enrolling in their program has a substantial impact on the number of students we include in the measure and the outcome of the measure itself. This issue is particularly thorny at four-year institutions. For this analysis, we look at capturing program enrollment at three points: in the fall of the first year, in the fall of the second year, and in the fall of the third year. Although a student at a two-year institution may be expected to complete by the third year if she is enrolled full time, we include this third-year measure as additional context for which students would be captured if a common measure were used for both two- and four-year schools.

The sooner that students declare a major, the more accurately we capture outcomes. For example, if a student drops out of school after her first year, a program completion measure that starts in the fall semester of sophomore year would not incorporate her outcomes. Yet, as we move closer to the point of student enrollment, we capture substantially fewer students who have declared a major. The tension between these two measures is illustrated in figure 1.

FIGURE 1

Share of Students with a Declared Major over Time

For students first enrolled in fall 2011



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Source: Urban Institute analysis of State Council of Higher Education for Virginia data.

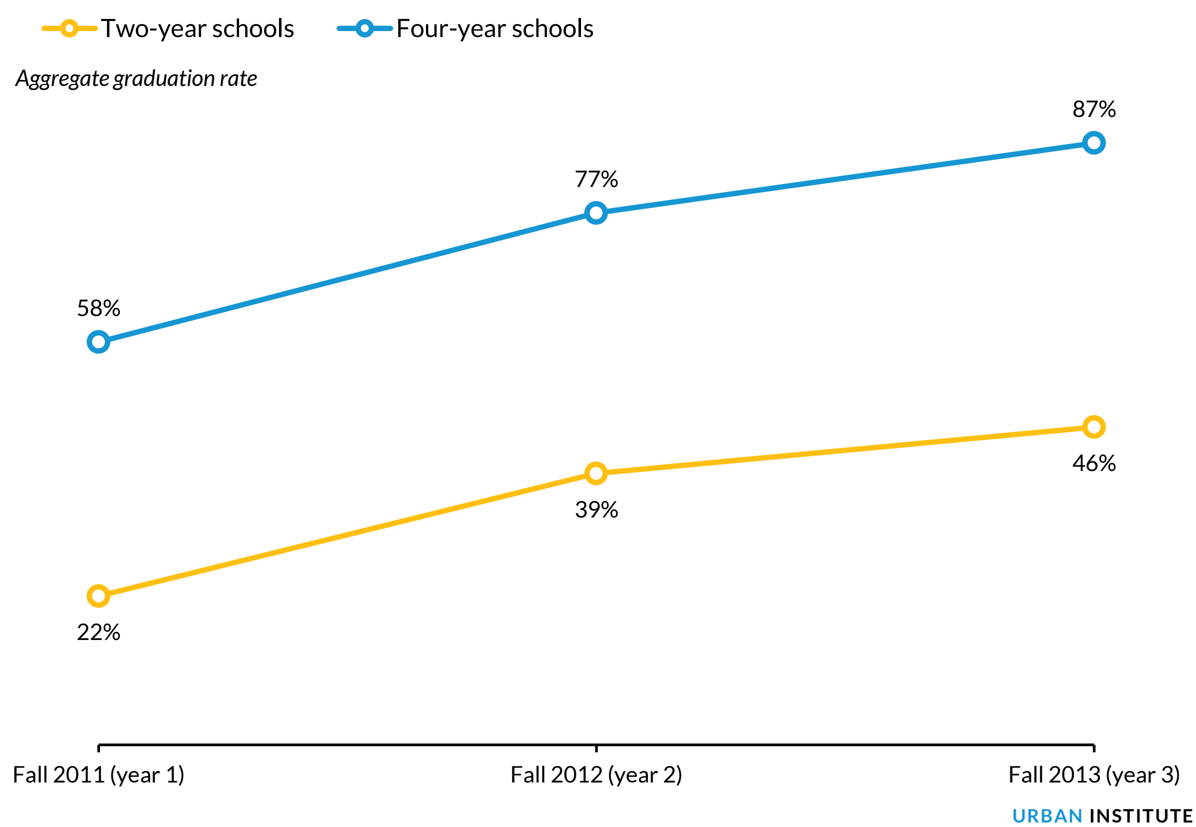
In two-year schools in Virginia, all students declare a major or program upon enrollment. Thus, 100 percent of students are enrolled in a measure that starts in the fall semester of the student's first year. But at four-year schools, just 68 percent of students have declared a major in the fall of their first year. In the fall of their second year, this share increases to 79 percent, but this figure is only the share of students currently enrolled (i.e., did not leave the institution in their first year). The share of ever-enrolled students with a declared major in the fall of their second year is 62 percent (reflecting students with both declared and undeclared majors who stopped out). Ninety-six percent of students still enrolled in four-year institutions have declared a major by the fall of their junior year, but this is still only 67 percent of ever-enrolled students.

Because students may leave the institution at any point after initial enrollment, the actual measurement of graduation rates also varies by the point at which major declaration is captured. If we look at enrollment at the start of a student's enrollment, we capture the "true" graduation rate after six years. But as we move the point at which we capture a student's declared major, we lose the accuracy of our program graduation measure because we cannot count the outcomes of students who left (figure 2).

FIGURE 2

Program-Level Graduation Rates

Rates rise when program participation is captured later in enrollment



Source: Urban Institute analysis of State Council of Higher Education for Virginia data.

The aggregate graduation rate for students in two-year schools nearly doubles, from 22 percent to 39 percent, when we capture program enrollment in the second year, rather than in the first year. Similarly, in four-year schools, the graduation rate leaps from 58 percent to 77 percent from the fall of the first year to the fall of the second year. And of students who are still enrolled in the institution in the third year, 87 percent graduate.

Four-year institutions in Virginia appear to have a great deal of autonomy over when students may declare a major, as there is no clear pattern for when institutions require their students to declare. One might expect that more selective colleges allow their students more time to declare, but this is not always the case. Although data from the University of Virginia and the College of William and Mary show that less than 40 percent of students who enrolled in 2011–12 had declared a major by the fall semester of sophomore year, 100 percent of students at Virginia Tech and Washington and Lee University had a declared major at that point.

Our goals for deriving a single measure include comparability with institution-level graduation rates and comparability across institutions. For two-year schools, these criteria can be easily satisfied by using the student's first-year fall major as the starting point for a program completion rate metric. But for four-year schools, none of these three time periods allows us to satisfy both conditions. A first-year metric would yield comparable institution graduation rates but would exclude 42 percent of first-year students. Likewise, a later measure would include more current students but would move the measure farther from a comparable institution-level completion metric. Later, we outline recommendations that could address this mismatch in the future. For the remainder of our analysis, we use the fall second-year measure for four-year institutions and the fall first-year measure for two-year institutions.

We select this sophomore-year measure for four-year schools because it strikes a balance (albeit uneasy) between the need to include as many students as possible and the need to reflect institution-level graduation rates. Moreover, it is possible that sophomore-year measures could be adjusted with institution-level freshman retention rates, a data point collected nationally in Integrated Postsecondary Education Data System data. For example, if 10 percent of students leave the institution by the end of their freshman year, policymakers could adjust the rates using the freshman retention rate. If policymakers assume that freshman-year dropouts would select into majors in the same proportions as their continuing peers, the adjustment is fairly simple: each program-level graduation rate would be multiplied by the share of students who stopped out (i.e., 100 percent minus the freshman retention rate). This adjustment would create a metric comparable with the two-year metric.

How Consistent Are Measures over Time?

Now that we have identified when we can capture students within a program of study, we must ascertain the stability and reliability of our estimates of program-level completion rates. Instability in this metric would emerge primarily from cohort size. A cohort of 10 students, for example, would experience a 10 percent drop in its completion rate if a single student stopped out. In contrast, a cohort of 100 students would experience only a 1 percent drop for losing a single student.

We develop program-level graduation rates for four consecutive cohorts. To estimate variability, we use the sample standard deviation for the program's rates over the four years. The standard deviation measures dispersion across four data points. The more a program's completion rates vary from the mean completion rate over the four years, the higher the standard deviation. This approach, although it satisfies our criteria for using simple, understandable measures, has downsides. First, for programs with mean rates near 0 or 100 percent, standard deviation estimates may be lower than actual because there is a floor (0 percent) and a ceiling (100 percent) for variation. Second, this standard deviation measure could mask actual improvement (e.g., a substantial increase in program-level graduation rates over time) as random variability.

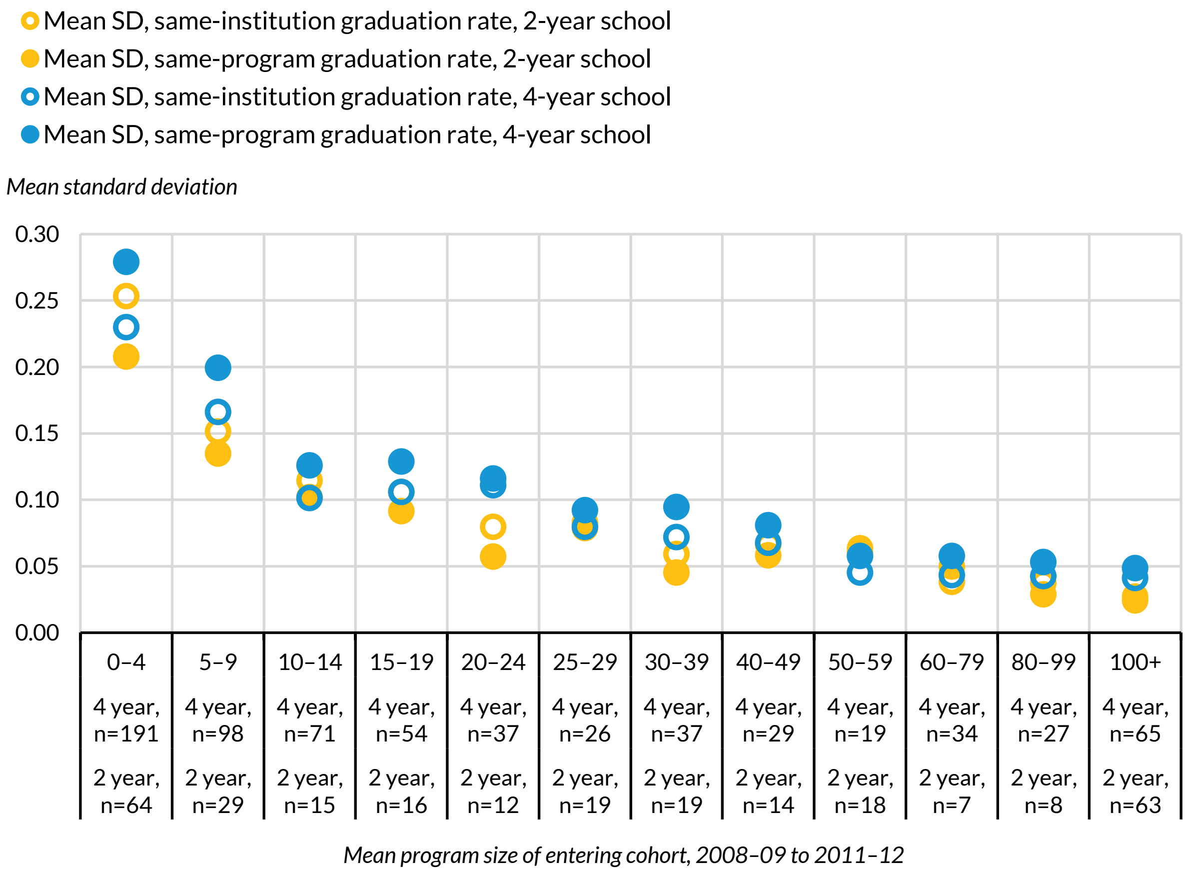
We investigate two methods for countering variability. First, we look at the potential of further aggregating programs by field category, creating larger groups by pooling similar fields. Second, we look at the potential to reduce random error by adding additional years of data.

In general, the lower the standard deviation, the less variability we find in the measurement. Figure 3 shows the average standard deviation for graduation rates of two-digit CIP code programs of different sizes in Virginia. We look both at same-program graduation and same-institution graduation (i.e., we count any graduation from the institution, not just within the two-digit CIP category). Notably, for students who entered the institution from 2008–09 to 2011–12, 191 four-year programs and 64 two-year programs had an average annual cohort size of four or fewer students. Across four years of graduation rate metrics, the typical standard deviation in graduation rate is relatively high: 0.23 for same-program graduation from a four-year institution and 0.25 for same-institution graduation for a program within a two-year institution. As cohort sizes increase, same-institution graduation rate standard deviations tend to decrease, moving below an average 0.10 standard deviations starting with a cohort size of 25 to 29 students. Programs that have standard deviation of around 0.10 in institution-level graduation rates tend to have comparatively stable graduation rate patterns but may still exhibit fluctuation (e.g., graduation rates of 100, 100, 80, and 100 percent have a standard deviation of 0.1, while graduation rates of 60, 40, 43, and 28 percent also have a standard deviation close to 0.1).

FIGURE 3

Program-Level Graduation Rates and Program Size

Graduation rates, measured across four cohorts, tend to stabilize as programs grow larger than 25 to 29 students



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Source: Urban Institute analysis of State Council of Higher Education for Virginia data.
Note: SD = standard deviation.

Within the same size groupings, we observe a divergence between the within-institution and within-program measures. For four-year schools, the variability of same-program graduation rates tends to be higher than for the same programs' within-institution graduation rates. In contrast, programs in two-year schools have higher variability for same-institution graduation rates and less variability for within-institution rates. This contrast may emerge from our different time period selections (fall of first year for two-year schools and fall of second year for four-year schools). But structural differences in program selection in two- and four-year schools may also play a role. Since students in two-year schools declare a program of study at the outset, program administrators more acutely monitor when students leave a program than administrators at four-year schools. Two-year schools may be more likely to try to stabilize program-level completion rates if they observe substantial year-over-year changes.

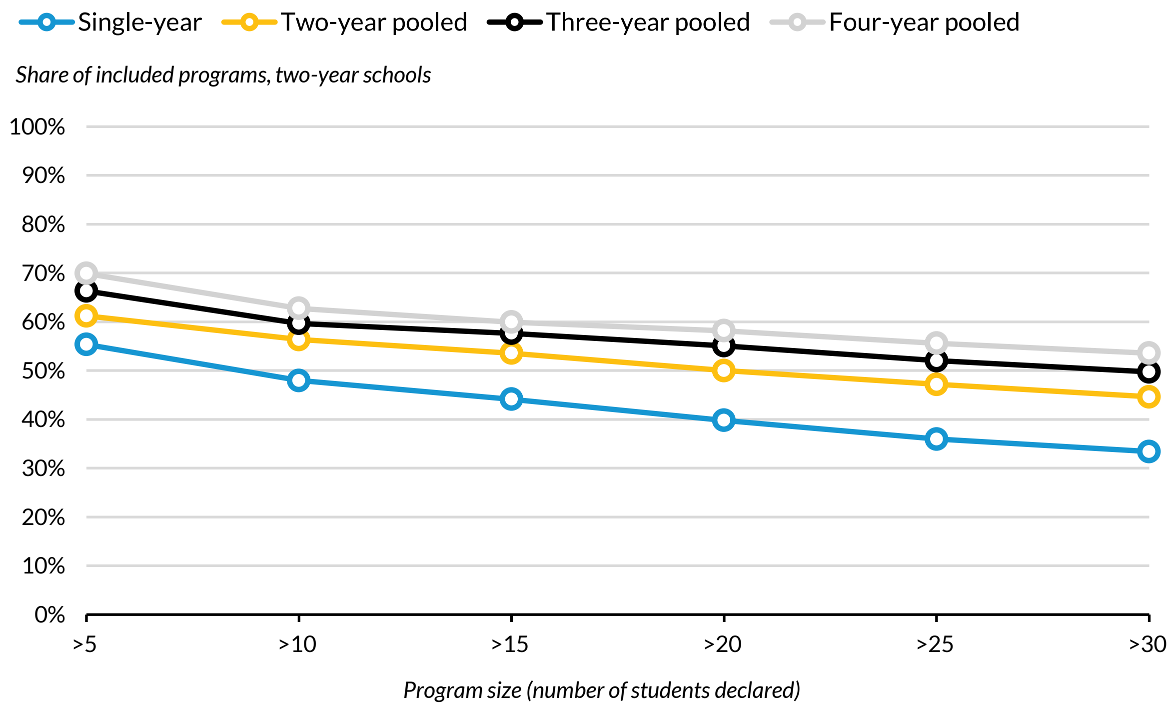
When we group our program categories into higher-level categories, arranged around 12 field clusters, we do not observe substantial changes in these variability patterns. The standard deviation starts to dip below 0.10 for cohorts of 25 to 29 students, and we observe the same pattern in within-institution and within-field variability for these higher-level categories. Fields of study in two-year schools tend have more variability in the same-institution graduation rate, while those in four-year schools tend to have more variability in the same-field graduation rate. We do not observe the same pattern when grouping programs at four-year schools into STEM and non-STEM categories, but this may be because of the small number of institution categories.

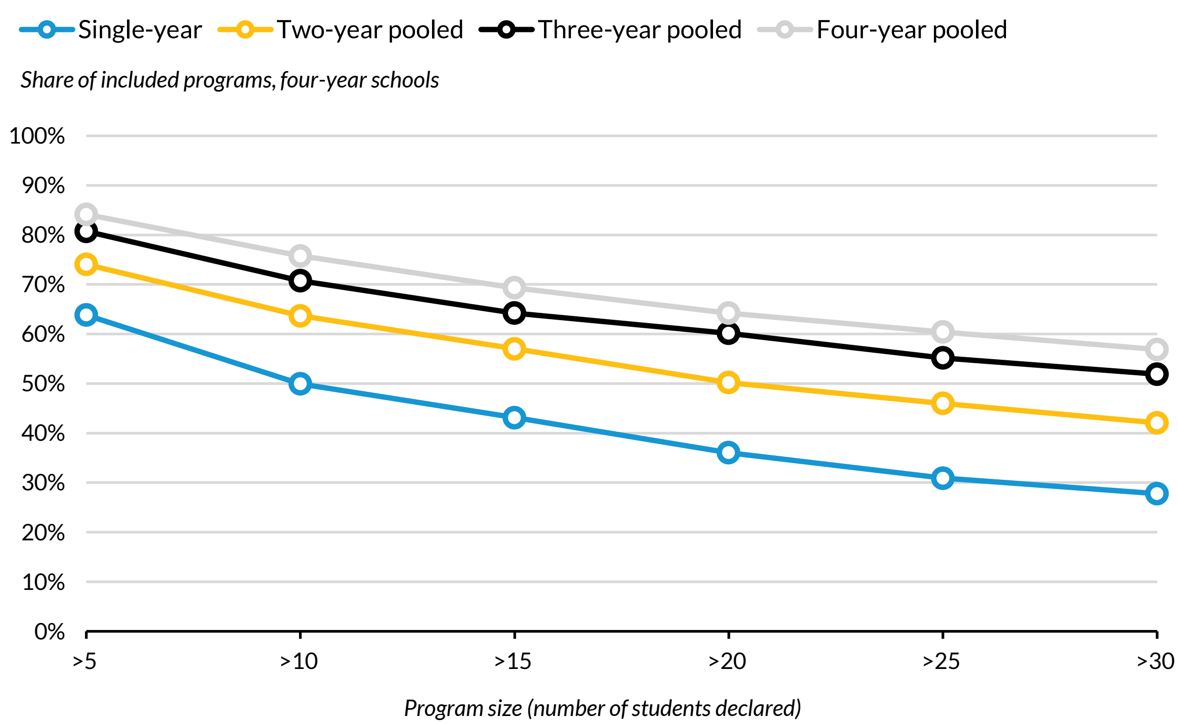
Our analysis of variability indicates that our field-level graduation metrics are most stable when the number of students in the cohort is above 25 or 30. This is consistent with a general statistical rule of thumb, which states that a sample size of at least 30 is needed to generate an accurate sample mean of a population, when the underlying population is presumed to be roughly normally distributed. But only using programs with 30 or more students in a given year would limit the number of programs (and students) we could create metrics for. One option is to pool multiple years of data, such that a program that has 20 students each year would have 40 with two years of pooled data or 60 with three years. We pool using a weighted average, such that a program with 10 students one year and 20 in another would have proportionally more weight put on the high-enrollment year. To assess the utility of pooling these data, we look at the number of programs and the number of students who would be included when we pool up to four years of cohort data (figure 4).

FIGURE 4

Effects of Pooling Years on Program Eligibility for Measurement

Pooling two years of data tends to boost the share of included programs by 10 to 15 percentage points





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Source: Urban Institute analysis of State Council of Higher Education for Virginia data.

When looking at two-digit CIP codes, we find that conducting a two-year pool substantially boosts the share of programs included in different program size cutoffs. For example, going from one to two years of data increases the number of programs at four-year schools with more than 20 declared students by 14 percentage points (from 36 percent to 50 percent) and the number at two-year schools by 10 percent percentage points (from 40 percent to 50 percent). Further pooling produces comparatively smaller gains in the share of programs included at each *n*-size. Programs at four-year schools tend to have a slightly higher share of programs that have at least five students, but the share of programs that meet subsequent size thresholds tends to drop off more quickly.

Notably, even with four years of pooled data, only 57 percent of programs at four-year schools and 54 percent at two-year schools have programs with 30 or more students. Although some programs may be left out because they have so few students in each of our cohort years, programs may also be excluded because the programs were either initiated or closed during our study period (pooling more years was limited or impossible). Further, at four-year schools where most students declare majors in their junior year, programs that eventually grow to larger cohort sizes may not have been included in our metric for the fall of the second year.

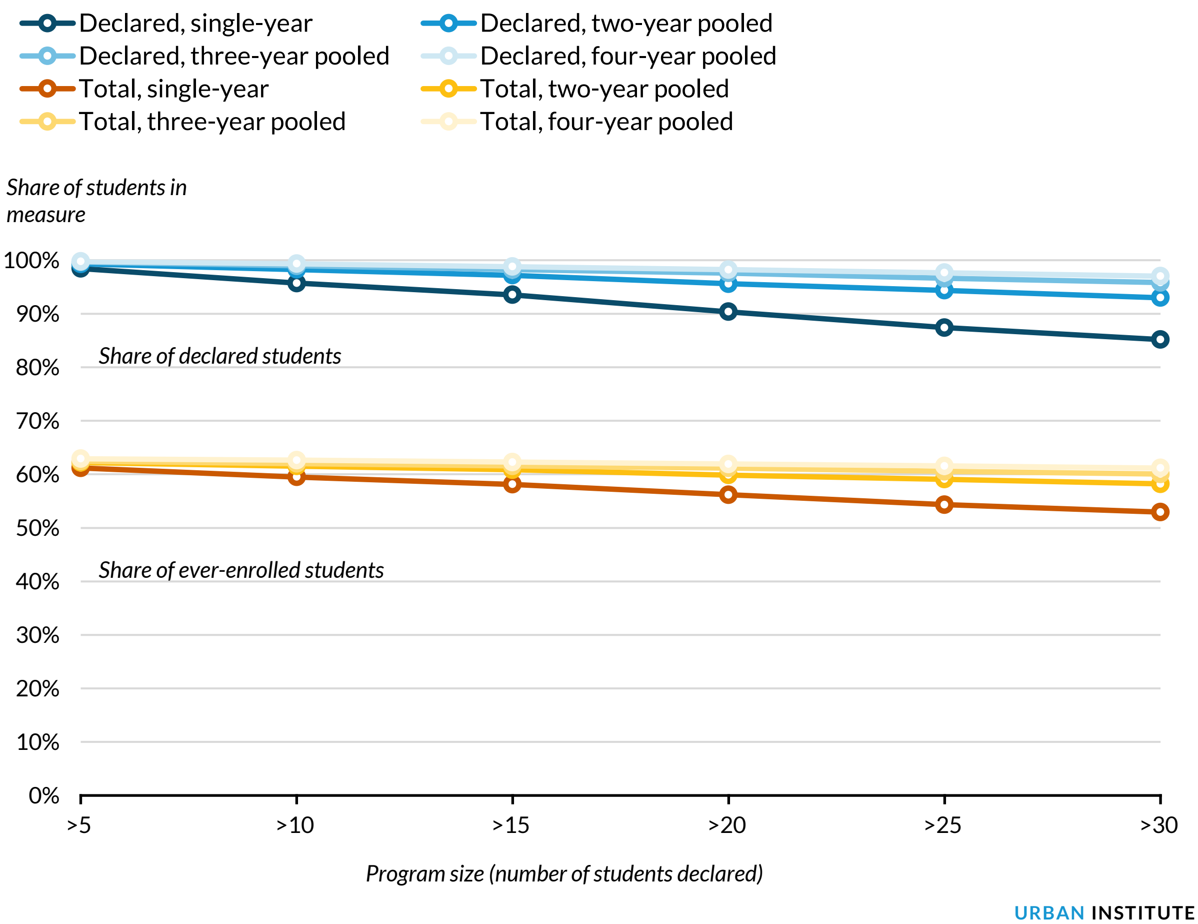
If we selected a cohort size cutoff of 30 students and a maximum pool of four cohorts, we would still exclude 43 percent of two-digit CIP programs in four-year schools and 46 percent of programs in two-year schools. Although this is a large number of programs, the share of excluded students is much lower. This is particularly true at two-year institutions. For example, 99.1 percent of students in two-year schools would be included in the program-level graduation rate metric in a pooled four-year measure with a minimum cutoff of 30 students (at the same cutoff with a single year of data, 95.4 percent of students are included).

Within four-year institutions, the share of students included, even with a pooled four-year cohort measure, is lower. The issue for four-year institutions is further complicated by the fact that a substantial number of students have either stopped out or have not selected a major, at the fall second-year mark. Figure 5 demonstrates the share of students with a declared major and the share of ever-enrolled students who are included in a metric for four-year schools with the major measured in the fall semester of sophomore year. At the 30-student cohort level, 85.2 percent of declared students are included in the one-year metric and 97.1 percent of students are included in the four-year pooled metric. But when we consider the share of ever-enrolled students, this number decreases substantially: 52.9 percent of ever-enrolled students are included in the one-year metric, and 61.1 percent of ever-enrolled students are included in the four-year pooled metric. Similar to our analysis of the share of programs included, we see the largest jump in the share of programs included when we shift from one year to two years of pooled data. Adding a third or fourth year of data produces only marginal increases in the share of included students.

FIGURE 5

Effects of Pooling Years on Student Eligibility for Measurement

The share of included students increases substantially with the pooling of two years, but adding a third and fourth year of data does not increase the share



Source: Urban Institute analysis of State Council of Higher Education for Virginia data.

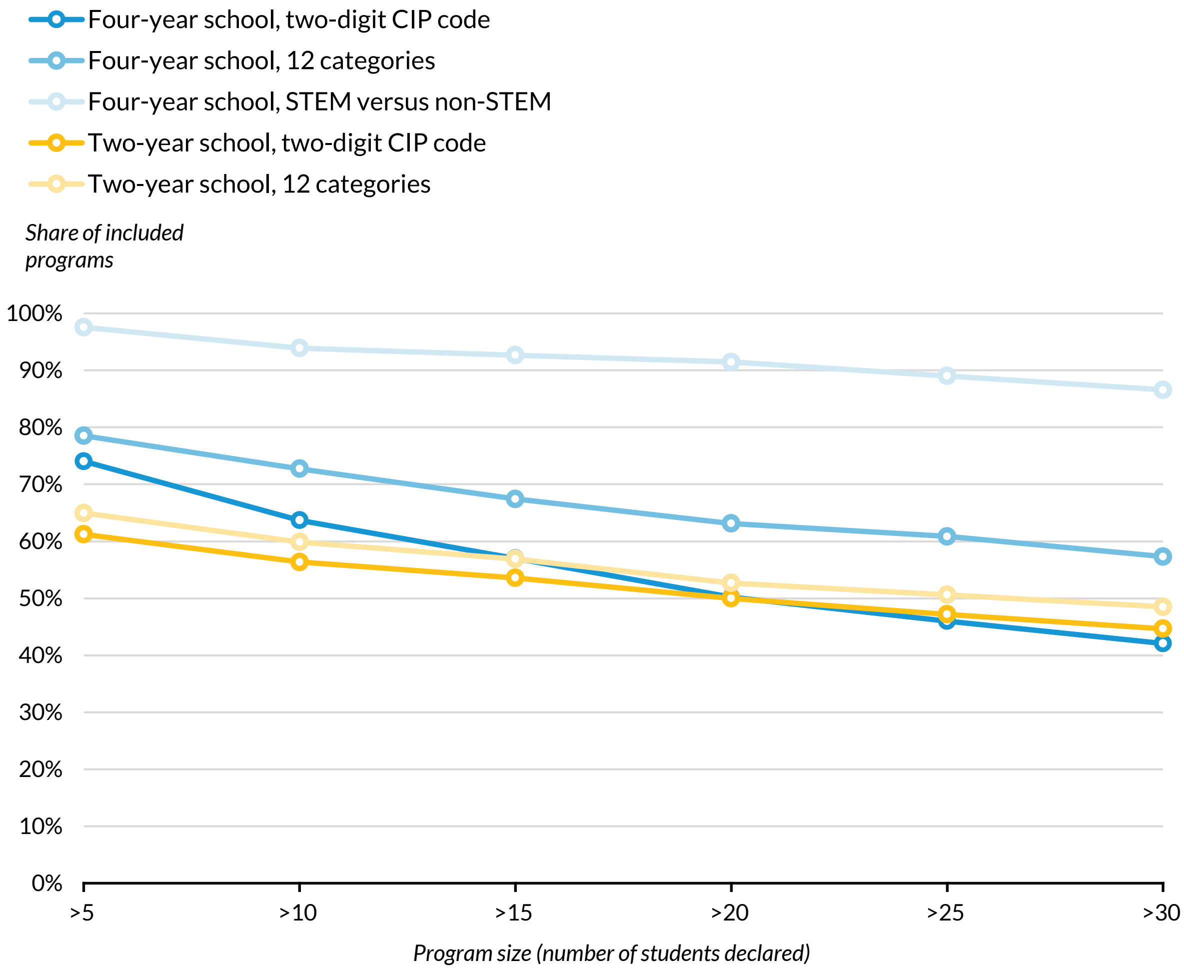
Another way to increase the size of cohorts we consider in our analysis would be to use substantially larger groupings of programs. By rolling up our two-digit CIP analyses into even larger categories, we could yield larger cohorts and more stable year-over-year estimates. For this analysis, we use the two-year pooled sample because it provides the largest boost in included two-digit CIP code programs. Figure 6 demonstrates how rolling two-digit CIP codes into 12 categories of majors and how rolling programs at four-year schools into STEM and non-STEM programs affects the share of respective higher-level program categories included in our measure at different cohort sizes. Moving from 47 two-digit CIP codes to 12 broad categories tends to matter more at four-year schools, where the share of program categories that have a cohort of at least 30 students increases from 42 percent to 57 percent. This move makes less of a difference at two-year schools, where the increase in the share of program categories included rises from 45 percent to 49 percent. Similarly, the increase in the number of students with a declared program is higher for students at four-year schools (from 93.0 percent to 97.5 percent for cohorts with more than 30 students) than for students at two-year schools (98.1 percent to 98.4 percent). When we move from considering the 12 categories to 2 categories (STEM or non-STEM) for four-year schools, the share of included categories increases dramatically. Eighty-seven percent of STEM or non-STEM categories have more than 30 students in a pooled two-year cohort.

From these analyses, we find that pooling into a two-year cohort yields the largest increase in cohort size. Subsequent years of pooling do not yield the same increases. Further, including more years of data may mask improvements or deteriorations in program-level graduation rates over time. Moving from 47 to 12 program categorizations provides some improvement in the share of four-year programs included in a pooled two-year metric but substantially less improvement for two-year schools. Broadening the categorization into STEM and non-STEM majors allows nearly all four-year STEM and non-STEM programs to be included but also requires a substantial loss of information.

FIGURE 6

Effects of Grouping Programs by Category on Share of Included Programs

Grouping programs by category increases the share of included programs, but these groups reduce the utility of program graduation rates



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Source: Urban Institute analysis of State Council of Higher Education for Virginia data.
Note: CIP = Classification of Instructional Programs; STEM = science, technology, engineering, and mathematics.

A strong measure of program-level graduation rates should include as many students as possible and should provide an accurate picture of the outcomes students should expect from that program. Our analyses indicate that programs with fewer than 25 or 30 students have substantial year-over-year variation in graduation rates, making a single-year metric inaccurate. From this point forward, we use a two-year pooled graduation rate measure, combining data for students who first enrolled in the institution in 2010–11 and 2011–12. Where a program has fewer than 30 students in the two-year pooled dataset, we add a third year (2009–10) or a fourth year (2008–09) to the pooled metric. If, after four years of pooled data, we do not have a cohort of at least 30 students, we do not report the program-level graduation rate. According to our previous analyses, this metric should include the programs that 97 percent of students enrolled in four-year institutions have selected and 99 percent of students enrolled in two-year institutions have selected. This measure leaves out a substantial number of students at four-year schools (39 percent) who have either left their institution or not yet declared a major.

Does the Student Graduate in the Given Field?

A critical question undergirding the development of program-level graduation rates is how these rates can add value for potential students and for policymakers. These rates can help policymakers understand selection into a program of study (e.g., do students who opt into a nursing program have better completion rates than those who apply to a business program?). Or they can help students understand whether they will succeed in the program they have selected (e.g., do students who opt into a nursing program actually get a nursing degree?). If these numbers are generally similar across different types of programs, or if students generally do not switch majors, it may not matter whether we look at one metric or the other. But if there are differences, we must understand how these differences play out.

TABLE 2

Differences between Institution and Program Graduation Rates

	Number of programs	Average institution graduation rate (%)	Average program graduation rate (%)	Average difference (percentage points)
Two-year programs				
Business, management, marketing, and related support services	30	19.2	14.8	4.4
Liberal arts and sciences, general studies, and humanities	23	22.6	17.8	4.8
Computer and information sciences and support services	21	17.5	13.1	4.4
Homeland security, law enforcement, firefighting, and related protective services	21	17.1	13.9	3.2
Health professions and related programs	17	29.0	23.6	5.4
Engineering technologies and engineering-related fields	14	18.9	13.2	5.7
Engineering	10	25.0	12.4	12.6
Mechanic and repair technologies and technicians	10	24.0	19.8	4.2
Four-year programs				
Psychology	30	78.0	66.1	11.9
Social sciences	30	79.6	69.0	10.6
Biological and biomedical sciences	29	77.5	61.9	15.7
Business, management, marketing, and related support services	29	72.5	62.5	10.0
Visual and performing arts	26	73.9	63.9	10.0
English language and literature and letters	24	79.2	67.1	12.1
Health professions and related programs	22	74.3	63.8	10.5
History	21	78.1	66.5	11.6
Computer and information sciences and support services	19	70.9	56.8	14.2
Physical sciences	19	75.7	55.1	20.6
Liberal arts and sciences, general studies, and humanities	16	79.6	51.1	28.5
Communication, journalism, and related programs	15	78.7	68.2	10.5
Parks, recreation, leisure, and fitness studies	15	71.6	61.8	9.8
Mathematics and statistics	14	77.7	55.2	22.5
Homeland security, law enforcement, firefighting, and related protective services	13	66.8	60.0	6.8
Multi- and interdisciplinary studies	13	75.3	50.4	24.9
Education	12	68.1	53.2	14.8
Engineering	12	74.3	60.5	13.8
Public administration and social service professions	12	76.1	65.0	11.1

Source: Urban Institute analysis of State Council of Higher Education for Virginia data.

To assess whether within-institution or within-program completion rates are more useful, we look at differences in these rates by two-digit CIP category in fields where several institutions offer these programs (table 2). Institution-level graduation rates are, by definition, equal to or greater than program graduation rates. But we do observe variations in this difference. Programs that have a STEM focus (e.g., mathematics and statistics, engineering, biological and biomedical sciences, and physical sciences) tend to exhibit larger gaps in the share of students who graduate at all, relative to the share of students who graduate with a degree in that major. We also see more students switch majors in broad-based fields in four-year schools, such as liberal arts and sciences and multi- and interdisciplinary studies. This may reflect the use of these fields as a "parking lot" for students who have not yet fully declared their field or may indicate some other kind of attrition.

Although both measures have value, this analysis indicates that the likelihood of graduating from the same declared program appears to vary depending on program categories. Differences in STEM and non-STEM fields, in particular, make this within-program measure a salient metric for students, policymakers, and researchers. In presenting our initial findings, we focus on this within-program measure, but we provide within-institution measures in the appendix for comparison.

Initial Findings from Program Completion Rate Data

Our test of the various aspects of a program-level graduation rate have yielded a single metric, for which we present some high-level descriptive statistics. Our final metric, although slightly different for two- and four-year institutions (differences in italics), is as follows:

- **Two-year institutions.** Within-program completion rates, *captured in the fall semester of the first year*, at the two-digit CIP level, pooled in two-year cohorts. For programs that do not have more than 30 students in a two-year pooled cohort, we add a third and fourth year of data to reach the 30-student threshold. Programs that do not reach the 30-student threshold with four years of data are excluded from the analysis.
- **Four-year institutions.** Within-program completion rates, *captured in the fall semester of the second year*, at the two-digit CIP level, pooled in two-year cohorts. For programs that do not have more than 30 students in a two-year pooled cohort, we add a third and fourth year of data to reach the 30-student threshold. Programs that do not reach the 30-student threshold with four years of data are excluded from the analysis.

At the outset, we identified five criteria for a strong measure of program-level completion rates. We assess how our metric aligns with these benchmarks:

- **Include as many students as possible.** We have outlined the tension, in four-year institutions, between when entry into a program major is captured and the share of students represented in the metric. Our selection of the fall semester of sophomore year attempts to strike a balance between these competing priorities, though it is not perfect. We capture all students in two-year schools with our fall-semester-freshman-year metric. Another concern is developing a strategy to capture completion rates in small programs. Our staged-cohort pooling strategy helps us recover some of these programs.

- **Provide an accurate and stable estimate of a student's likelihood of completion.** Our assessment of graduation rates at different cohort sizes indicates that 30 students is a stable estimate of completion rate. But our pooling method may mean our measure draws on up to four cohorts' data to generate an estimate. This strategy means our measure may obscure recent program changes that could increase completion rates for subsequent cohorts. Our selection of within-program graduation rate may generate more stable measurements, relative to within-institution graduation rates, at two-year schools, relative to four-year schools.
- **Be consistent across institutions.** With the exception of when we capture program enrollment, we have developed a measure that is consistent across all institutions. Our measure does exclude a couple of four-year institutions because of when most of their students declare a major (i.e., after the fall semester of sophomore year).
- **Align with institution-level graduation rates.** Our two-year metric aligns well with institution-level graduation rates, as students are captured as they start their enrollment. However, our four-year measure produces estimates that are generally higher than the institution-level graduation rate because it excludes students who drop out in their first year and students who do not declare a major in the fall semester of their second year. Further, our simplification of the period for completion, and cohort considered currently enrolled, may introduce more variation from graduation-level estimates.
- **Be intelligible to those who might enroll in the program.** We designed our metric to be comprehensible to students and policymakers. Some elements of our metric, such as the staged pooling, may be confusing, but we believe this rate will generally be comprehensible to a lay audience and useful for students considering a given major.

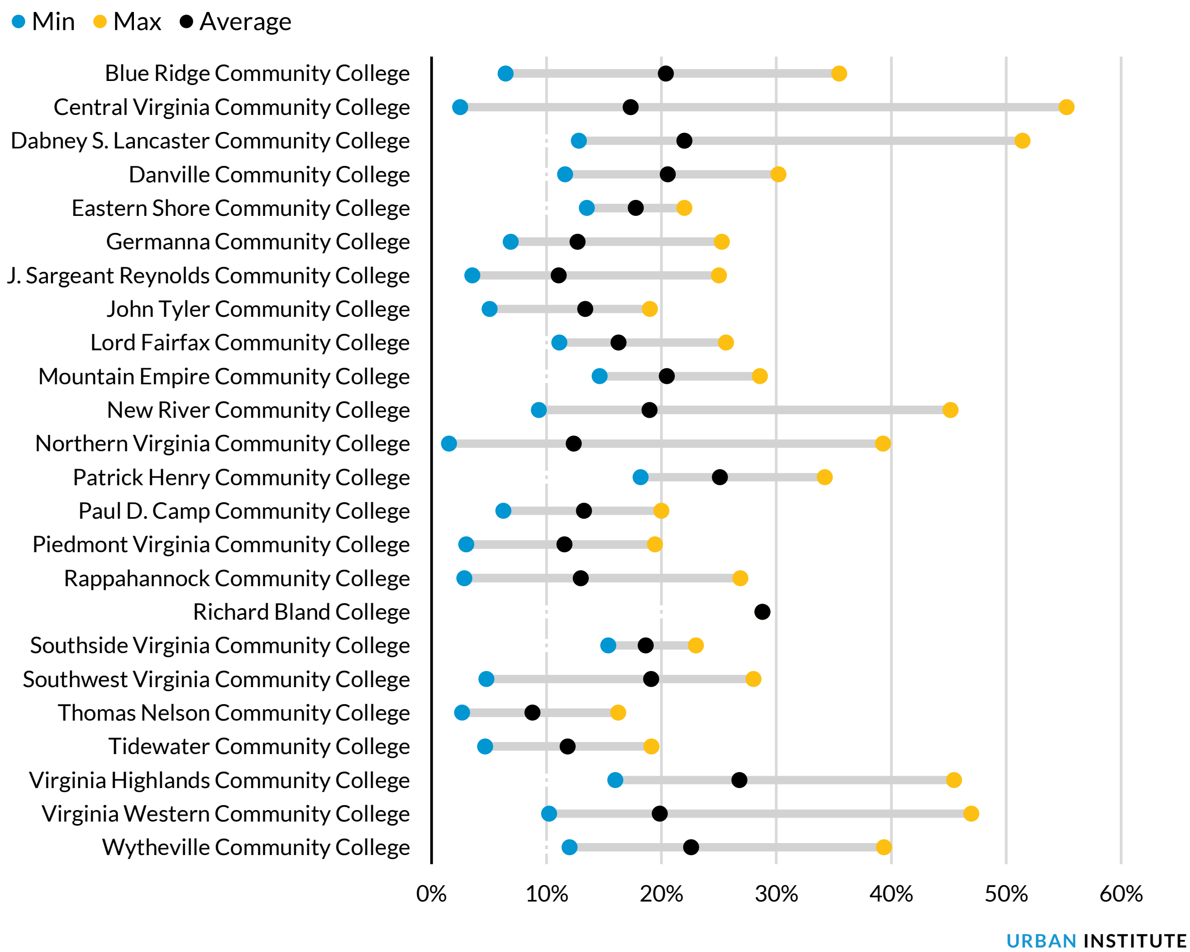
With these criteria in mind, we present preliminary findings from our metric. The limitations we outlined above apply to these findings. These findings illustrate what we could learn from these metrics, but they do not comprehensively describe program-level completion rates for all programs or students in Virginia.

Variation within Institutions

One area of interest for policymakers and researchers is the degree to which program-level graduation rates vary between institutions. We provide a high-level overview of this variation by looking at the lowest, highest, and average within-program completion rates by institution (figure 7). We observe substantial variation. In some institutions, this difference can be as high as 40 percentage points between the program with the highest graduation rate and the program with the lowest. This variation could reflect internal institutional dynamics, such as the type of student attracted to certain programs, the rigor of programs across the institution, and when students typically select majors (e.g., if they must complete introductory coursework).

FIGURE 7A

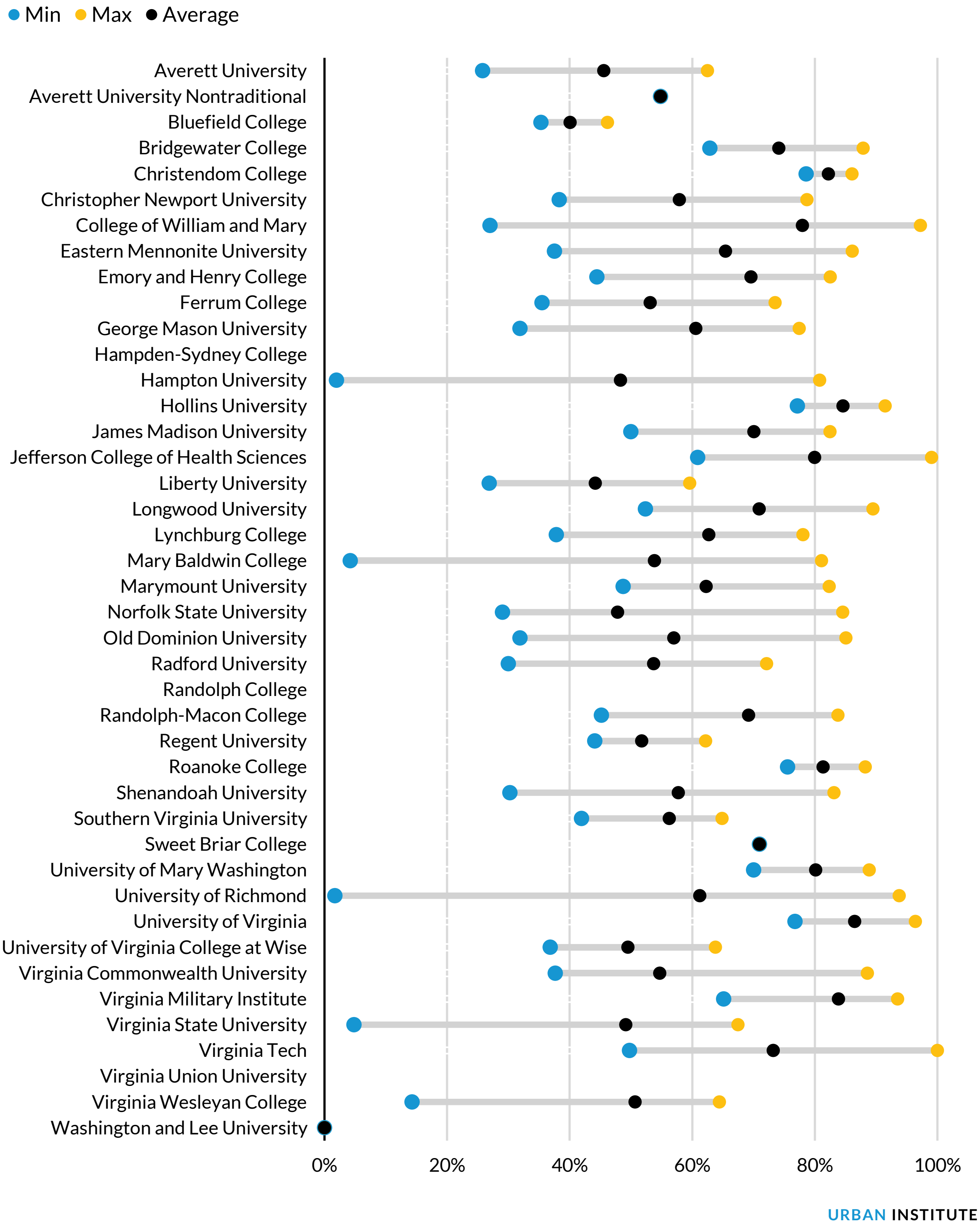
Within-Program Completion Rates, Two-Year Schools



Source: Urban Institute analysis of State Council of Higher Education for Virginia data.

FIGURE 7B

Within-Program Completion Rates, Four-Year Schools



Source: Urban Institute analysis of State Council of Higher Education for Virginia data.

These findings also highlight the limitations of our measure. Some institutions have no programs or only one program with a cohort large enough for a program-level graduation rate. This is largely because most students in these institutions did not declare a major until after the fall semester of their second year. Institutions with narrow variation in program-level graduation rates may have consistent graduation rates across programs but may also just have fewer available programs on which to demonstrate variation.

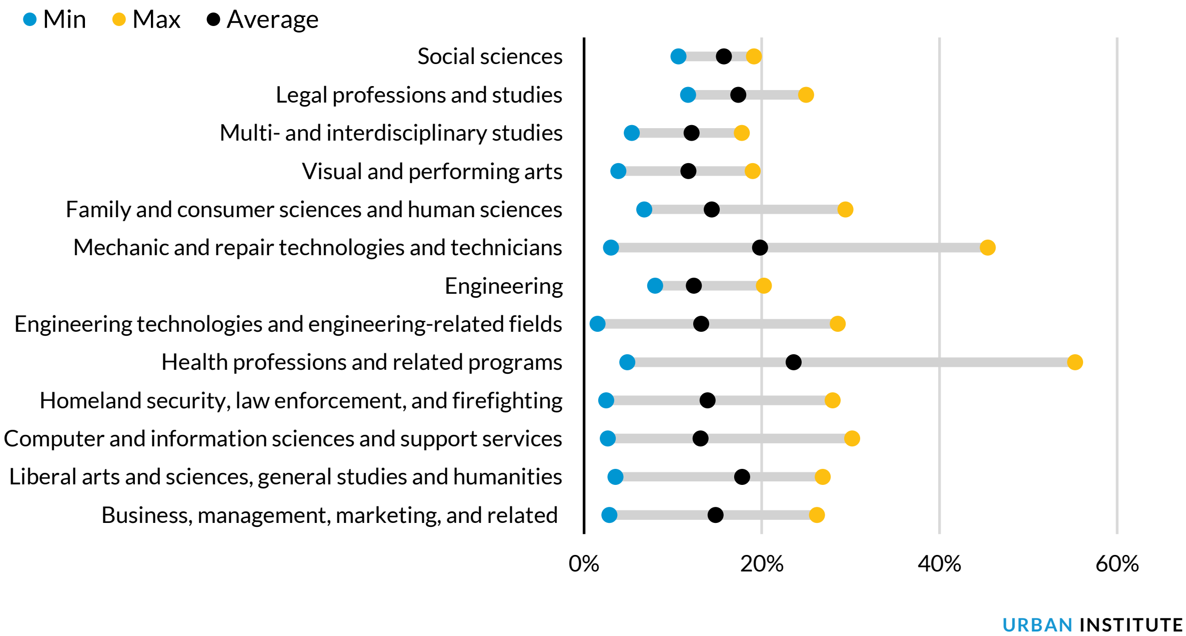
Variation within Programs

We look at variations in CIP programs for which we have at least five program-level graduation rates for a given two- or four-year school (figure 8). Similar to our institution-level estimates, we find more variation in programs for four-year schools, relative to two-year schools. This likely reflects lower graduation rates from two-year schools, according to our measure and variation in the selectivity of four-year institutions, which is highly correlated with completion rates.

Although we identified patterns in the likelihood of within-program graduation relative to within-institution graduation by type of major, it is difficult to discern similar patterns here. Because we are working with data from only one state, we do not have enough data to fully separate institutions by selectivity or by other metrics (e.g., the share of students receiving Pell grants). Breakdowns by these measures may provide more insight into the wide variation we find here and help us identify an average or typical graduation rate for a given program at two- or four-year schools with similar characteristics.

FIGURE 8A

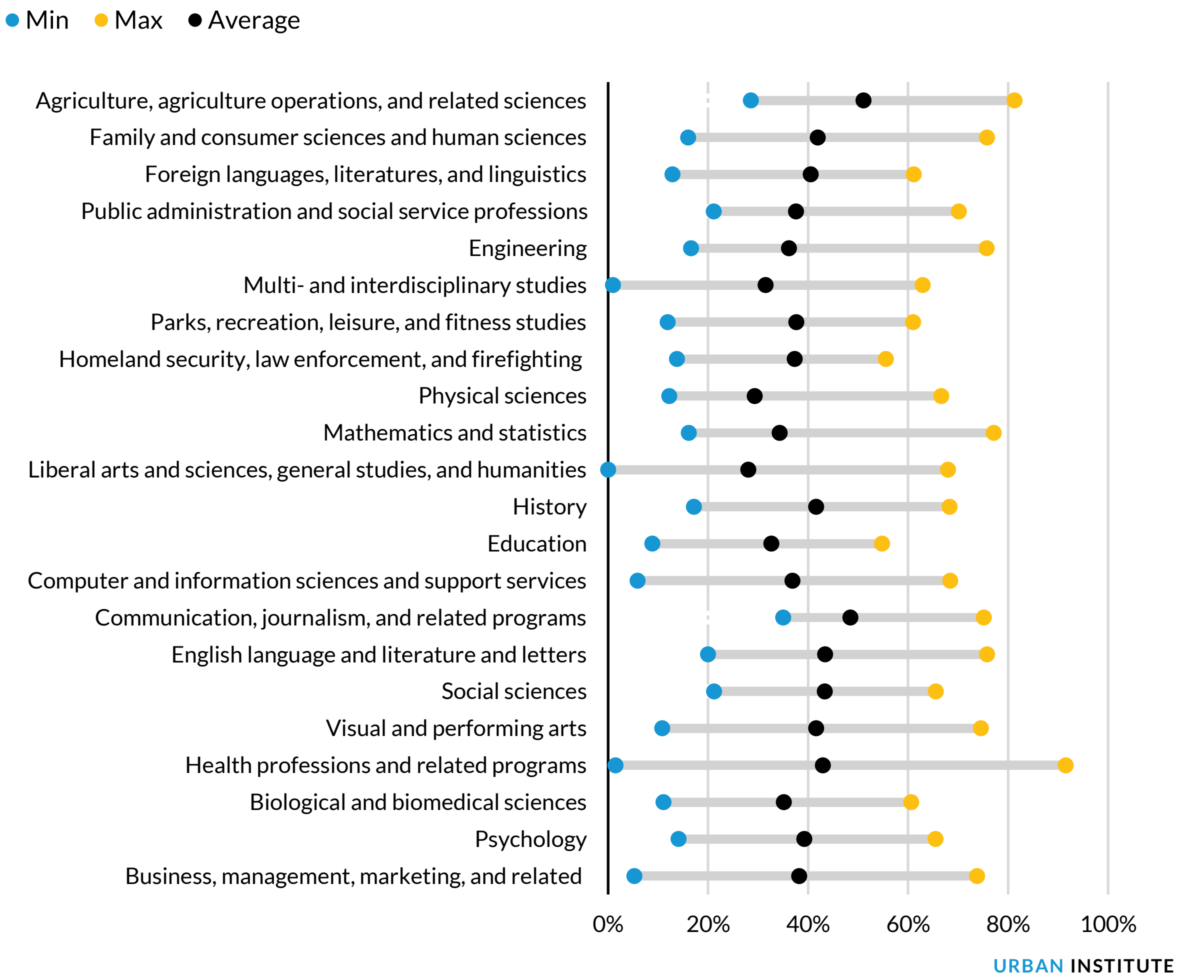
Between-Program Graduation Rates, Two-Year Schools



Source: Urban Institute analysis of State Council of Higher Education for Virginia data.

FIGURE 8B

Between-Program Graduation Rates, Four-Year Schools



Source: Urban Institute analysis of State Council of Higher Education for Virginia data.

Recommendations

Through our analysis, we have developed insights about what we would need, particularly from four-year institutions, to develop comparable and reliable program-level graduation rates. We summarize these insights into a set of recommendations for what policymakers might need to develop program-level graduation rates for a given state or for the nation.

- **Use pooled years to develop a sufficient cohort size.** This recommendation is in line with current practice for the College Scorecard, which pools two cohorts of data to produce many of its metrics. Program-level graduation rates, particularly in small schools, could require additional cohorts of data. Even with four cohorts, we still did not have sufficiently large program groups to develop measures for all students with a declared major. The more these data are pooled, the more accurate the metric may be for a typical student's chances of graduating from that program. But these additional pooled years would make it difficult for institutions or program leaders to improve graduation rates for small programs because the data are averaged with prior years' data.

- **Require students at four-year schools to declare a major earlier.** The development of accurate program-level graduation rates would have to come with a mandate for four-year schools. For an accurate measure, four-year schools must require students to declare a major by the fall semester of sophomore year, at the latest. For some schools, this could be a large shift, and the cost of mandating this change must be weighed against the potential gain from having these metrics. One potential midlevel step would be to require students to opt into a "metamajor"—a large group of potential majors, grouped by subject—similar to what is required of freshman at Georgia State University. This metamajor could be a program-level metric, allowing students the flexibility to select a more specific major later on.
- **Provide a clear distinction between within-program graduation rates and program-level within-institution graduation rates.** Student selection into a given program might have a differential effect on the within-program rate, relative to the within-institution rate. To align with earnings data, a within-program graduation rate makes the most sense (as earnings data are for students who graduated). But this rate may not reflect variations in the success of students who did not complete the major but completed another major. For example, a student who leaves a math and statistics program and enrolls in and graduates from an engineering program would likely be considered a positive outcome, even though she is not counted in the math program's graduation rate.

At first glance, developing a program-level graduation rate may seem like a natural next step to help students and policymakers understand program-level earnings. But developing this metric is fraught with potential potholes, particularly if policymakers cannot regulate decisions about program selection within institutions.

Appendix

TABLE A.1

Two-Digit CIP Codes Divided into 12 Categories

Two-digit CIP code	Two-digit CIP code description	Rolled-up code description
1	Agriculture, agriculture operations, and related sciences	Biological, agricultural, and environmental sciences
3	Natural resources and conservation	
26	Biological and biomedical sciences	
2	Architecture and related services	Architecture, construction, mechanics, and craftsmanship
46	Construction trades	
47	Mechanic and repair technologies and technicians	
48	Precision production	
49	Transportation and materials moving	
5	Area, ethnic, cultural, gender, and group studies	Social sciences
22	Legal professions and studies	
25	Library science	
28	Military science, leadership, and operational art	
33	Citizenship activities	
42	Psychology	
44	Public administration and social service professions	
45	Social sciences	
54	History	
31	Parks, recreation, leisure, and fitness studies	Fitness and protection
43	Homeland security, law enforcement, firefighting, and related protective services	
10	Communications technologies and technicians and support services	Computers, mathematics, and technology
11	Computer and information sciences and support services	
27	Mathematics and statistics	
29	Military technologies and applied sciences	
41	Science technologies and technicians	
12	Personal and culinary services	Personal and culinary studies
19	Family and consumer sciences and human sciences	
34	Health-related knowledge and skills	
35	Interpersonal and social skills	
36	Leisure and recreational activities	
37	Personal awareness and self-improvement	
13	Education	Education
14	Engineering	Engineering
15	Engineering technologies and engineering-related fields	
9	Communication, journalism, and related programs	Arts and humanities
16	Foreign languages, literatures, and linguistics	
23	English language and literature and letters	
24	Liberal arts and sciences, general studies, and humanities	
30	Multi- and interdisciplinary studies	
38	Philosophy and religious studies	
39	Theology and religious vocations	
50	Visual and performing arts	
40	Physical sciences	Physical sciences

Two-digit CIP code	Two-digit CIP code description	Rolled-up code description
52	Business, management, marketing, and related support services	Business
51	Health professions and related programs	Health

Notes: CIP = Classification of Instructional Programs. CIP codes that did not appear in the data were not considered for this roll-up.

TABLE A.2

Two-Digit CIP Codes, STEM versus Non-STEM

Two-digit CIP code	Two-digit CIP code description	Rolled-up code description
11	Computer and information sciences and support services	STEM
14	Engineering	
26	Biological and biomedical sciences	
27	Mathematics and statistics	
40	Physical sciences	
1	Agriculture, agriculture operations, and related sciences	Non-STEM
3	Natural resources and conservation	
4	Architecture and related services	
5	Area, ethnic, cultural, gender, and group studies	
9	Communication, journalism, and related programs	
10	Communications technologies and technicians and support services	
12	Personal and culinary services	
13	Education	
15	Engineering technologies and engineering-related fields	
16	Foreign languages, literatures, and linguistics	
19	Family and consumer sciences and human sciences	
22	Legal professions and studies	
23	English language and literature and letters	
24	Liberal arts and sciences, general studies, and humanities	
25	Library science	
28	Military science, leadership, and operational art	
29	Military technologies and applied sciences	
30	Multi- and interdisciplinary studies	
31	Parks, recreation, leisure, and fitness studies	
32	Basic skills and developmental and remedial education	
33	Citizenship activities	
34	Health-related knowledge and skills	
35	Interpersonal and social skills	
36	Leisure and recreational activities	
37	Personal awareness and self-improvement	
38	Philosophy and religious studies	
39	Theology and religious vocations	
41	Science technologies and technicians	
42	Psychology	
43	Homeland security, law enforcement, firefighting, and related protective services	
44	Public administration and social service professions	
45	Social sciences	

Two-digit CIP code	Two-digit CIP code description	Rolled-up code description
46	Construction trades	
47	Mechanic and repair technologies and technicians	
48	Precision production	
49	Transportation and materials moving	
50	Visual and performing arts	
51	Health professions and related programs	
52	Business, management, marketing, and related support services	
54	History	

Notes: CIP = Classification of Instructional Programs. CIP codes that did not appear in the data were not considered for this roll-up.

Notes

[1] Delece Smith-Barrow, "Education Dept. to Change College Scorecard, Be Less 'Prescriptive' with Accreditors, Officials Say," Education Writers Association blog, October 4, 2018, https://www.ewa.org/blog-educated-reporter/education-dept-change-college-scorecard-be-less-prescriptive-accreditors.

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