The AIR Professional File

Fall 2020 Volume

Supporting quality data and decisions for higher education.

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LETTER FROM THE EDITOR

Welcome to the Fall 2020 volume of the *AIR Professional File*! In this volume, you will find two articles whose authors use large databases from community colleges and statewide systems to address issues with significant policy implications.

It seems that debates have raged for decades over how to use completion rates to evaluate college performance. No matter what formula is adopted, the resulting computations often fail to reflect our diverse missions. What if we used a student-focused methodology instead? In his article, *Rethinking Completion Analytics to Better Support the Student Experience across Diverse Ecosystems*, Jeffrey L. Cornett proposes an approach to completion rates that adjusts to the institution's ecosystem and range of students we serve. Check out his CAT-scan graphics!

In their study *Brain Drain in Maryland: Exploring Student Movement from High School to Postsecondary Education and the Workforce*, Amber Bloomfield, Bess A. Rose, Alison M. Preston, and Angela K. Henneberger examine the migration of students who leave the state to attend college elsewhere. Which students are most at risk of not returning to the state workforce? Their analysis comprises a unique application of propensity score matching approach to better understand brain drain and mitigate its impact.

Wherever and however you are working these days, I hope you are healthy and happy. Soothe the stress of this ongoing health crisis by treating your brain to some new ideas. Share yours with your colleagues by sending a manuscript to the *AIR Professional File*.

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Rethinking Completion Analytics to Better Support the Student Experience across Diverse Ecosystems

Jeffrey L. Cornett

About the Author

Jeffrey L. Cornett, PhD, was executive director of institutional research at the central region of Ivy Tech Community College of Indiana from 2011 to 2017. He also served in the same capacity at Valencia College of Florida from 2007 to 2011. He is an expert in information engineering and the graphical display of data insights.

Acknowledgments

This research would not have been possible without the kind and thoughtful support of several people. I thank Dr. Sanford Shugart, president of Valencia College, for teaching me to value the student experience and the importance of finding ways to measure it. I am grateful to Dr. Sue Ellspermann, president of Ivy Tech Community College of Indiana for encouraging me to publish this article, and for allowing me to reveal all the Ivy Tech Central Indiana data shown in this paper.[1] Finally, Stephen Hancock earns my thanks for devoting several years of his career to building our CAT-scan data mart. This was an incredibly time-consuming and frustrating task since I continually added more layers to the CAT-scan graphs.

Abstract

Single measures of college performance fail to reflect the mix and diversity of students served. First-time students vary widely in terms of their readiness to succeed in college. Higher education environments (ecosystems) also vary widely and afford students differing admission and transfer opportunities. These factors confound college completion analytics when those who define college goals focus only on what is best for the college. A fresh way to rethink completion analytics would be to measure college completion success from the student point of view and how they wish to experience college. Student-focused completion rate scorekeeping would improve research into best practices. Student advising would also improve if completion analytics were disaggregated along a continuum of readiness to succeed.

Keywords: student experience, college readiness, CAT-scan graphs, college ecosystem, sister university, transfer rates, 1+3 transfers, 2+2 transfers, second-chance transfers, completion rates, vertical lift, right shift, institutional research, student advising

1. The Central Indiana service area of Ivy Tech Community College includes Indianapolis (Marion County) and eight surrounding counties (Boone, Hamilton, Hancock, Hendricks, Johnson, Morgan, Putnam, and Shelby). In 2017 Ivy Tech was reorganized statewide to formally eliminate the regional layer of management. The name "Ivy Tech" in this article refers to the Central Indiana region or service area of that college, unless otherwise noted.

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Article 150

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INTRODUCTION

In my first meeting with our college's new chief information officer I began to explain problems with completion performance scorekeeping. After patiently listening for a while, he interrupted to challenge me to prescribe the exact college scorekeeping formula that I proposed. At first, I did not know how to respond. Just changing the completion formula does not solve the problem. After pausing to think for a moment, I suggested that his question was the wrong one to ask. When judging success, it is not the *college* performance that matters—it is the *student* performance! We should try to analyze and improve how the student experiences college, and not merely how the college experiences students.

PROBLEM STATEMENT

Completion analytics that focus on the college experience rather than the student experience present us with three problems:

1| Students' goals might not match the college's goals. Colleges and their scorekeepers naturally want to experience students who have high rates of retention and completion. Students, however, when given the opportunity to transfer, might have different goals that make them choose to transfer before graduating from their first school attended.

2| Student mix varies across colleges. When analyzing college performance, it is much too convenient to incorrectly assume that all colleges have the same mix of students operating within comparable higher education environments. This false assumption allows all differences in performance outcomes to be attributed to the college, and none to the students. This oversimplifies comparisons across colleges and the interpretation of results. It is too easy to presume that higher-scoring colleges must simply have better leadership, academics, or support programs, and that lower-performing colleges must be doing something dramatically wrong or must be missing major improvement opportunities.

3| Single measures of college performance can mislead students and their advisors. Completion analytics that adjust to the mix of students served could also provide data that allow student advising to be better tailored to the individual student. Students are not all equally likely to succeed in college. Individual students vary in backgrounds, motivations, and abilities. Single performance measures for the college reflect the outcome for an average student at that college, and not a diverse range of individual students with their varying goals and conditions of learning.

RESEARCH HYPOTHESIS

Institutional research, college benchmarking, and student advising could all be improved if performance metrics were stratified along a continuous scale that reflects the range of diversity in a student's readiness to succeed.

This paper provides supporting evidence for this hypothesis through consideration of five research questions (see below for definition of terms):

1| Are 1+3 transfers successful at their transfer destination schools?

2| How much does the student experience vary between college-ready and college-prep students?

3| How does an ecosystem affect transfer behavior and student mix?

4| Can we improve our understanding of college readiness beyond just a ready-or-not split?

5| How do you show performance improvement when there are differences in student mix?

TERMINOLOGY

Ecosystem

The local mix of higher education opportunities varies for students across colleges and universities in different regions. A different mix of competing colleges, educational programs, and enrollment capacities can result in one region having a much different mix of first-year students who begin at community college rather than those who begin at the local state university. Second- and third-year educational pathways and capacities can also vary by region, resulting in much different student transfer behavior.

Three Types of Transfers: 2+2, 1+3, and Second-Chance Transfers

For those seeking a 4-year degree, 2+2 transfers are students who begin college at a 2-year school and graduate there first before transferring to a 4-year school.

1+3 transfers are students who did well academically at their first 2-year school, but who did not graduate there. Instead they chose to transfer to another school to continue their education toward a 4-year degree.

A third type of transfer are second-chance transfers, defined as students who did not do well academically at their first college and who earned very few credits before leaving. After leaving and perhaps even several years later, they found a second chance to continue their education elsewhere. Because second-chance transfers were not academically successful at their first school, these transfers should not be added into transfer-adjusted completion rates.

College-Ready vs. College-Prep Students

Not all high school graduates are academically prepared for college-level coursework. Community colleges sometimes use a placement test for their first-time-in-college students to identify those who would benefit from developmental coursework in basic reading, writing, and math before they take more-advanced college-level courses.

THEORY

Florida state colleges include some of the most respected community colleges in the country. Higher graduation rates lead to frequent performance awards, as well as the ongoing study by consultants and benchmarking organizations to learn the secrets to Florida's success. Valencia College in Florida is viewed as an exemplary role model, and that college won the inaugural Leah Meyer Austin Award in 2009 and the inaugural Aspen Prize for Community College Excellence in 2011.

Austin Community College in Texas, with high transfer rates and low graduation rates, provides an interesting contrast to Valencia College. Austin's scorekeeping problem was addressed by the president of Valencia College in his article, "Rethinking the Completion Agenda" (Shugart, 2013). Shugart's article introduces the term "ecosystem" to define the higher education environment and how students behave in different ways across diverse ecosystems. He offers a compelling essay that explains how low graduation rates can be driven by high transfer rates attributable to the local environment (ecosystem) and are not due to a deficiency in college leadership. He suggests the need for more-collaborative research of student behavior across colleges, including the development of measures of the performance of the entire ecosystem.

This paper builds on Dr. Shugart's working theories and provides additional supporting data.

METHODOLOGY

Case Studies

Two community colleges are the case studies for this paper. These two schools operate in much different higher education environments, but both are greatly affected by the admissions practices of their local sister state universities.

The Central Indiana region of Ivy Tech Community College is in an environment where it is easy for students to transfer out before graduation. Neighboring state universities do not require a degree before they admit successful students as transfers. Ivy Tech's retention and completion rates are scored very low.

Valencia College in Central Florida is in an environment where state policy strongly discourages state universities from admitting community college transfers that did not first graduate. Valencia College is an award-winning school with comparatively high rates of retention and graduation.

Valencia College provides an ironic contrast in strategies to Ivy Tech. The number one strategic priority at Valencia College is on student learning, and only secondarily on college completion performance metrics. Valencia leadership believes that greater learning will lead to better student performance. Conversely, with its low completion rates Ivy Tech has always been compelled to focus its strategic priorities on improving retention and completion. How do you get students to stay until graduation, and how do you get students to graduate sooner so that their completion can be included within the limited number of years used for performance scorekeeping?

Unique Sources of Data

During our study both colleges had good sources of data and capable institutional research (IR) departments. This allowed us to analyze and compare the student experience in ways that go well beyond traditional college scorekeeping formulas.

Ivy Tech had built a data mart that tracked all first-time-in-college students over an 11-year period using data from the National Student Clearinghouse (2005–15). This allowed us to study transfers in terms of their long-term outcomes and to explore whether the individual student's choice to transfer was beneficial or harmful to that student.

Valencia College routinely differentiated graduation rates between college-ready and college-prep students. Ivy Tech adopted a similar approach for internal research and reporting. This differentiation enabled us to make comparisons in and across both schools on how student readiness to succeed affects graduation rate performance.

Each community college had a close relationship with its local sister state university. This included coordinated research on issues of common interest. The admissions practices of local sister state universities affect the aptitude mix of students attending the local community college. In both Central Indiana and Central Florida, applicants who are not admitted to their state university as freshmen often start at the local community college with the goal of transferring to the local state university as soon as they are allowed to do so. Data on the aptitude or achievement levels of entering students at sister state universities are available online from websites that have been designed to aid students in college selection.

Valencia's sister university is the University of Central Florida (UCF), a school with high admission standards and low transfer-out rates. Due to rapid growth, UCF has always had very limited enrollment capacity to accept transfers-in as sophomores.

Ivy Tech's sister university is Indiana University–Purdue University Indianapolis (IUPUI), a regional campus shared by Indiana University and Purdue University. As a regional campus, IUPUI's admissions standards are naturally lower than their two separate main campuses. IUPUI, with high rates of transfers out (including transfers to one of their main campuses), had the available enrollment capacity to easily accept students to transfer in well before those students had completed a degree.

CAT-Scan Methodology

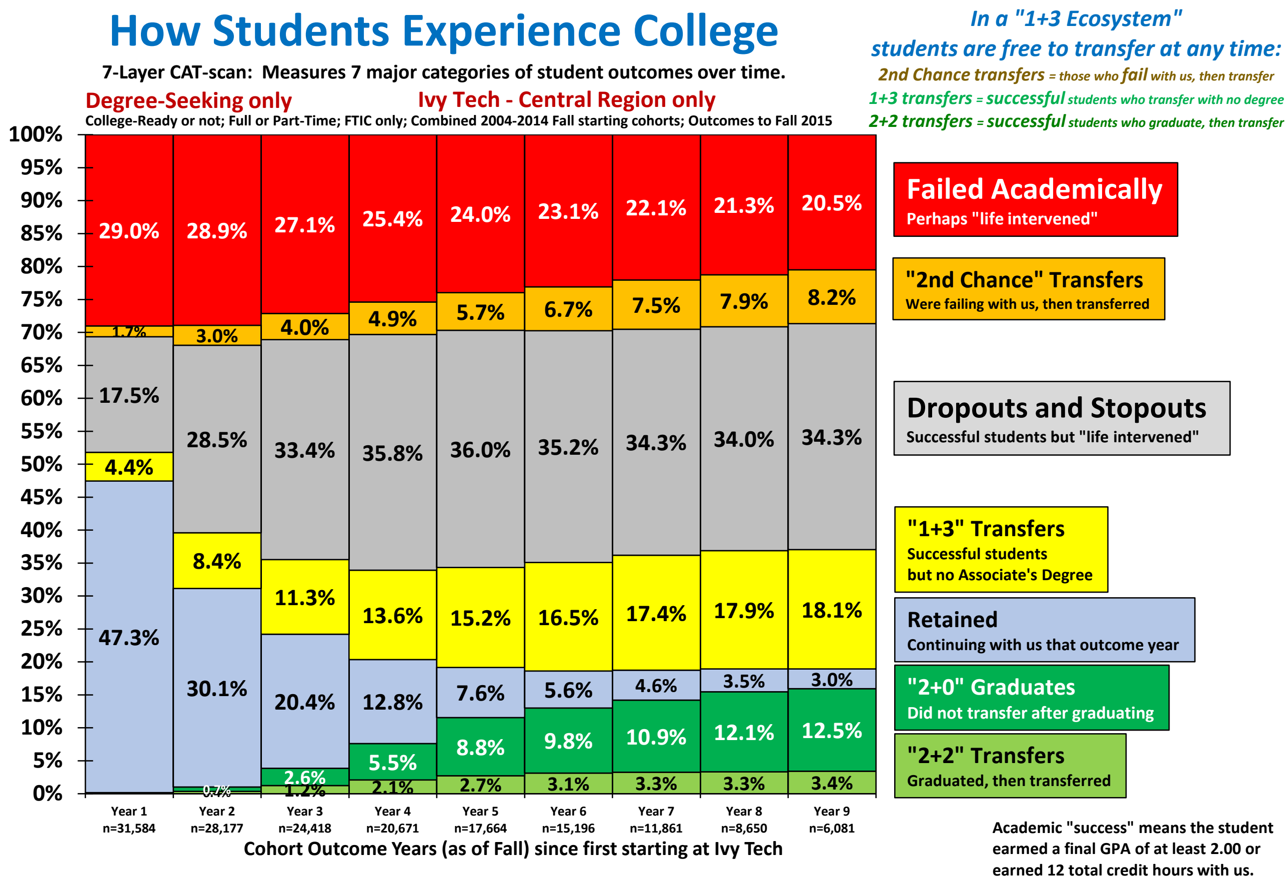
The first question asked when considering a graduation rate is, "Why isn't it higher?" The simple answer is that the students did something else. Yet it is rare to see a graduation rate reported at the same time that all other student outcomes are reported. It helps to graphically show all student outcomes in layers that add up to 100%. If you want more students to graduate, a 100% layered graph encourages you to consider how to get fewer students to do anything else.

Ivy Tech pioneered the use of CAT-scan (Cohorts Across Time) graphs to show the diverse ways students experience college. A CAT-scan graph simultaneously shows all student outcomes for all cohort outcome years. Ivy Tech built these CAT-scans (Cornett & Hancock, 2015) by first creating a data mart that matched up all annual starting cohorts of students against each student's cohort-year outcomes as recorded in the National Student Clearinghouse.

Ivy Tech IR staff invested many months of effort to design and create their original CAT-scan data mart. Their effort increased every year as the variety of reported student outcomes expanded. Once the data mart had been created, the big reward was the ease by which precomputed outcomes could instantly be reported and disaggregated across any student group or research treatment variable. The data mart was delivered in a spreadsheet that could be explored using simple pivot-table methods. In a single afternoon, IR staff can produce scores of CAT-scan graphs. The hardest part is labeling the graphs and delivering the results so that users can understand all the information made available to them.

Figure 1 is a basic 7-layer CAT-scan graph. Three different types of transfers are shown: 2+2, 1+3, and second-chance transfers. When studying a CAT-scan, it is useful to consider how results vary across cohort outcome years. In this example, by the end of Year 3 few students have graduated (3.8% = 1.2% + 2.6%; areas in light green and dark green), while more have had a successful 1+3 transfer (11.3%; areas in yellow).

Figure 1. This 7-layer CAT-scan combines 11 starting cohorts across 9 cohort outcome years.



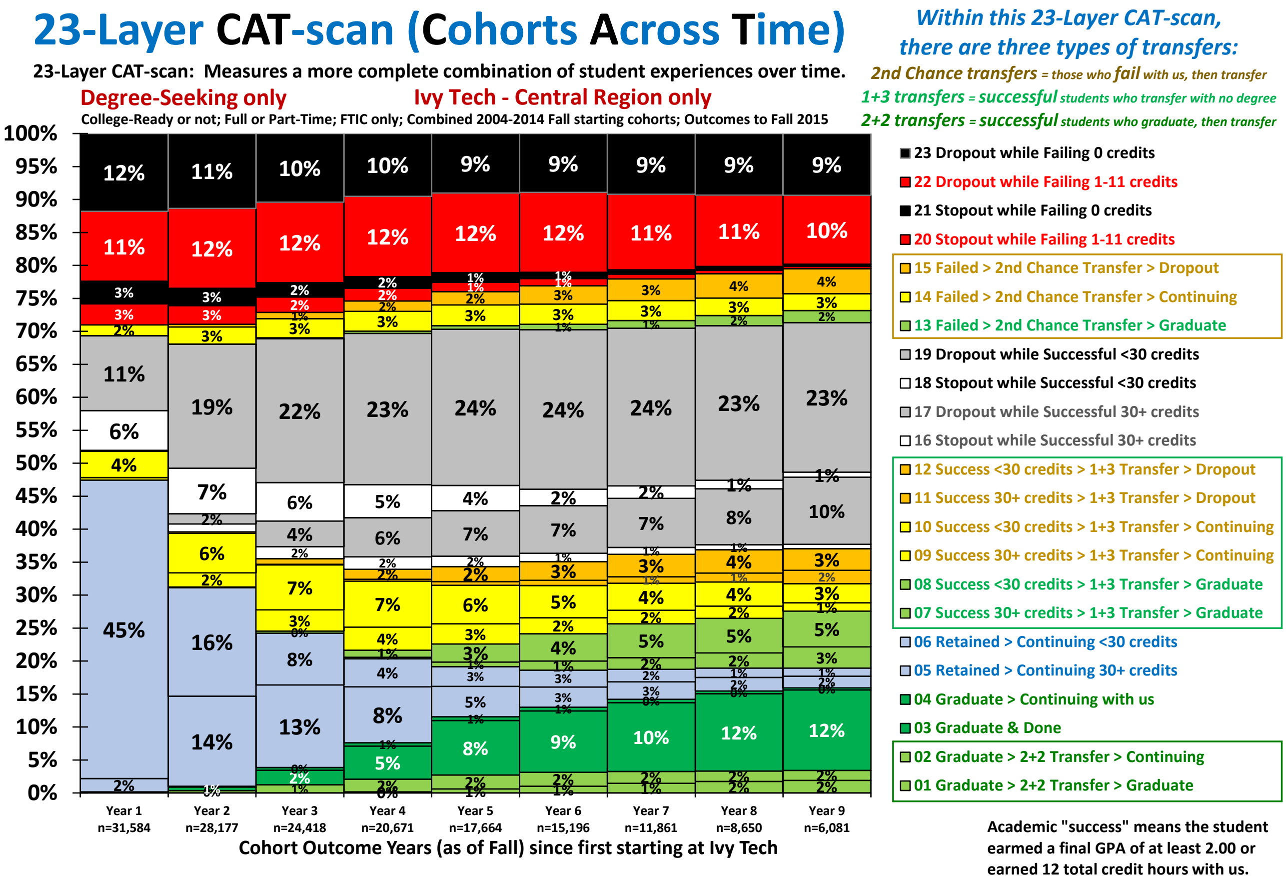
IPEDS (Integrated Postsecondary Education Data System) serves as the national standard for benchmarking the performance of colleges. The National Center for Education Statistics (2020) recently began reporting community college completion outcomes out to 6 and 8 years instead of just 3 years, as was their previous standard.

As seen in Figure 1, Ivy Tech's 8-year outcomes show an obvious improvement in graduation rates over 3-year outcomes. Even so, after 8 years the 1+3 transfers (17.9%) are still more common than all graduates (15.4% = 3.3% + 12.1%) from Ivy Tech.

Second-chance transfers also increase over time. In the first outcome year, few students who fail academically show up as transfers in National Student Clearinghouse data. By Year 8 many initial college failures can be seen to have returned to school elsewhere to give college another try.

Answering one research question often leads to asking two new questions, and new questions quickly arise when first considering a 7-layer scan. The National Student Clearinghouse provides data that allow researchers to know much more about student outcomes. Additional research variables can be linked from a college's own data warehouse. Ivy Tech eventually built a 23-layer CAT-scan to study a much richer variety of student outcome questions (see Figure 2).

Figure 2. A 23-layer CAT-scan shows many more types of outcomes than a basic 7-layer CAT-scan.



In this 23-layer CAT-scan, 1+3 transfers are disaggregated into three transfer-destination outcomes: students who have graduated, those continuing in school somewhere, and those who have dropped out. Each of these three categories is further split between those who earned at least 30 credits before leaving and those who transferred out before earning 30 credits. This combination of six outcomes within the 1+3 transfer type allows us to explore a wide range of what-if scorekeeping questions.

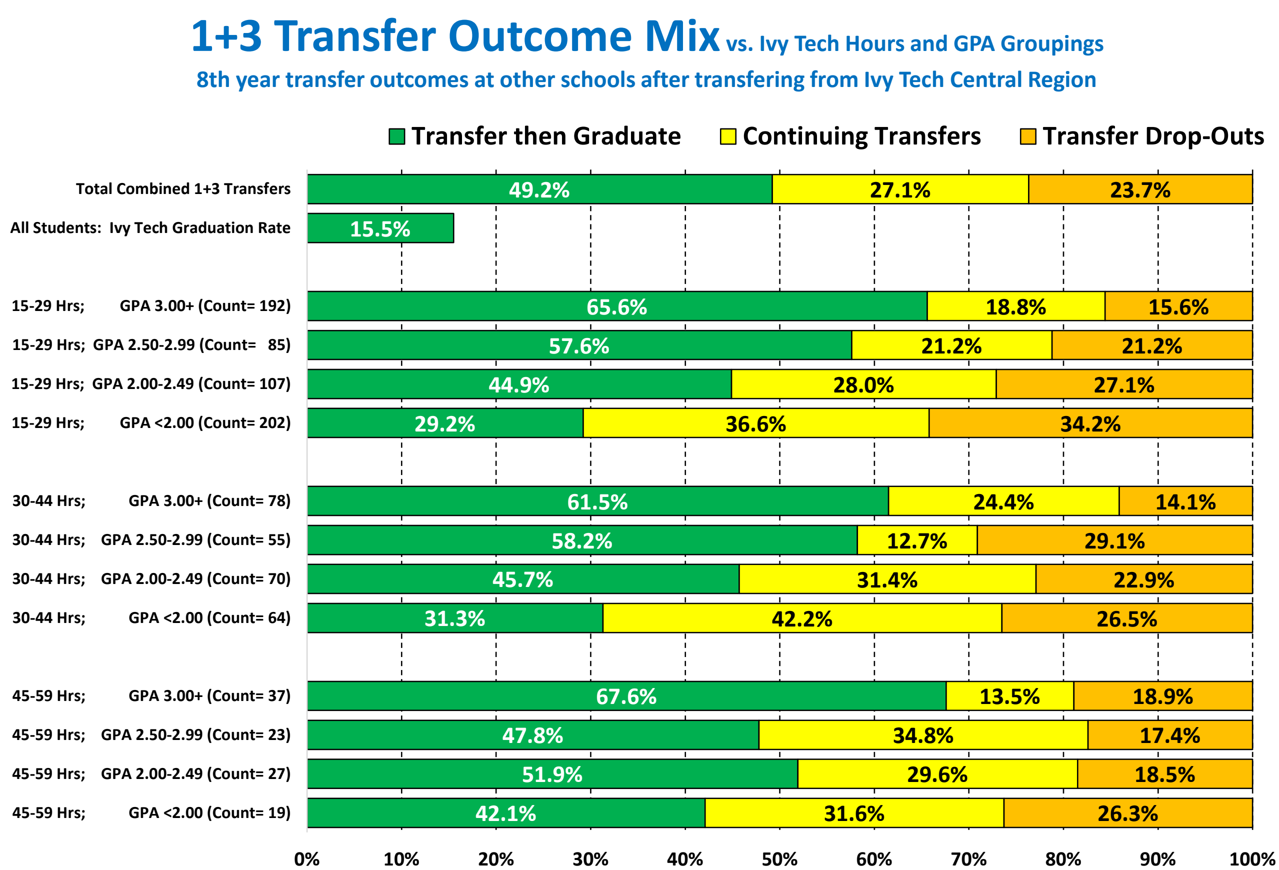
For example, Indiana considered the creation of a 30-credit transfer certificate that could be earned by students who completed the right mix of freshman-level courses. That certificate would be interpreted by scorekeepers as a type of pretransfer completion credential. The use of 30-credits-earned layers in the 23-layer CAT-scan shows how the introduction of a 30-credit transfer certificate might affect college completion rates, and how these rates would vary depending on how many cohort years are counted in the scorekeeping.

RESEARCH QUESTION 1: ARE 1+3 TRANSFERS SUCCESSFUL AT THEIR TRANSFER DESTINATION SCHOOLS?

Although transfers before graduation damage a college's reported performance, the important question is whether 1+3 transfers hurt a student's performance. Do academically successful students who transfer before graduating have good rates of completion and persistence after leaving Ivy Tech?

Ivy Tech studied graduation, retention, and dropout rates for 1+3 transfers as of the eighth cohort year after starting at Ivy Tech. These results were disaggregated across categories for Ivy Tech grade point average (GPA) and credit hours earned (Cornett et al., 2016) (see Figure 3). Ivy Tech GPA appears to have a strong influence on success after transfer.

Figure 3. 1+3 transfer outcomes at destination schools show high rates of graduation and persistence.



Overall, students who transferred out 1+3 style earned a degree somewhere else at a rate of 49.2%. This is more than three times the 15.5% rate that all students starting at Ivy Tech graduate from Ivy Tech with an associate degree. Not all 1+3 transfers complete, but most (76.3%) either graduate (49.2%) or are still in school (27.1%) when measured over an 8-year horizon since first starting at Ivy Tech.

The effect of additional hours earned at Ivy Tech on success after transfer is uncertain. This study included both full-time and part-time students. Part-time students naturally need more years to graduate than full-time students, and many part-time students persist in school as long as needed to complete their degree.

With relatively high rates of graduation and persistence in school after transfer, it is difficult to regard 1+3 transfers as mistakes from a student's perspective.

RESEARCH QUESTION 2: HOW MUCH DOES THE STUDENT EXPERIENCE VARY BETWEEN COLLEGE-READY AND COLLEGE-PREP STUDENTS?

Community colleges have open admissions standards. All high school graduates who apply are admitted. This includes the full range of students in terms of their readiness to succeed in college, ranging from straight-A students to those with poor grades who barely graduated.

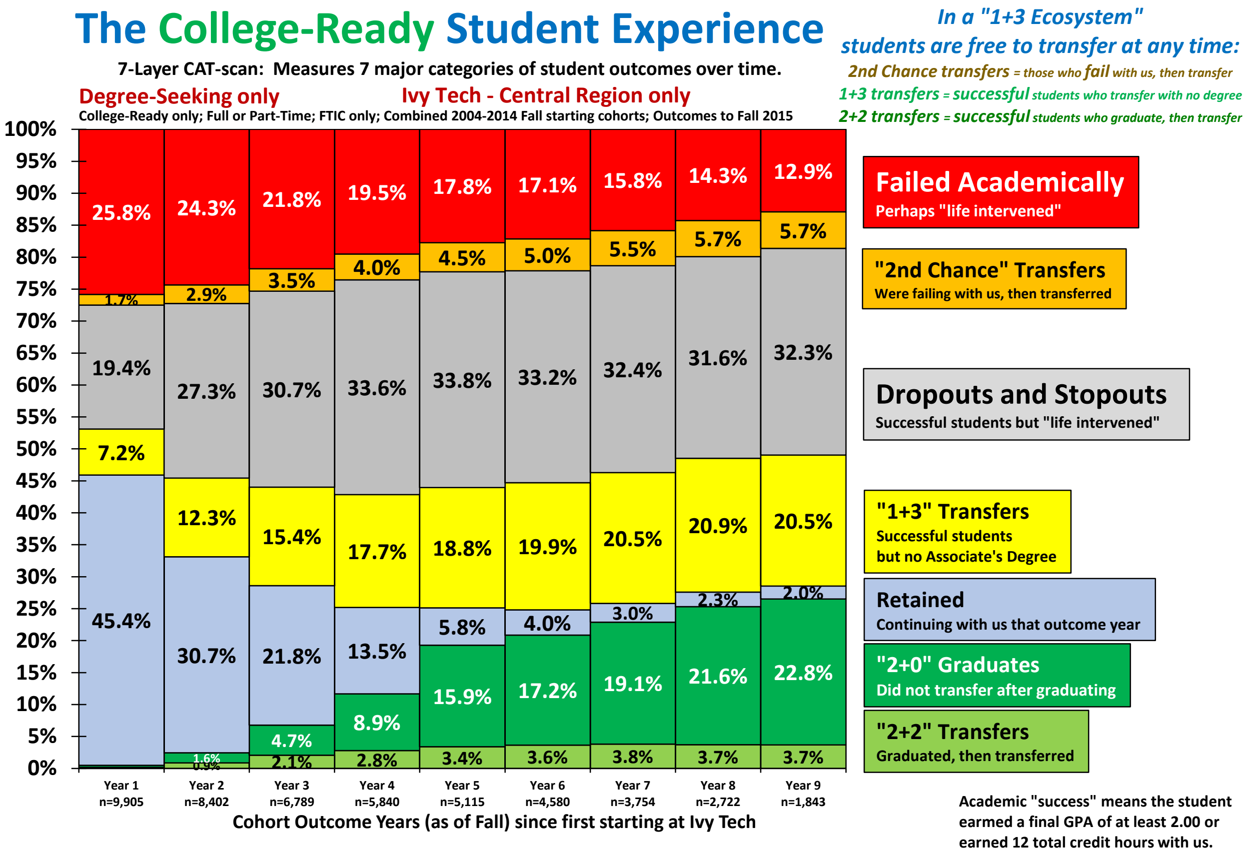
It seems intuitively obvious that students who are better prepared for college will generally succeed in college at higher rates; this hypothesis still needs to be researched and measured. How much better do college-ready students perform?

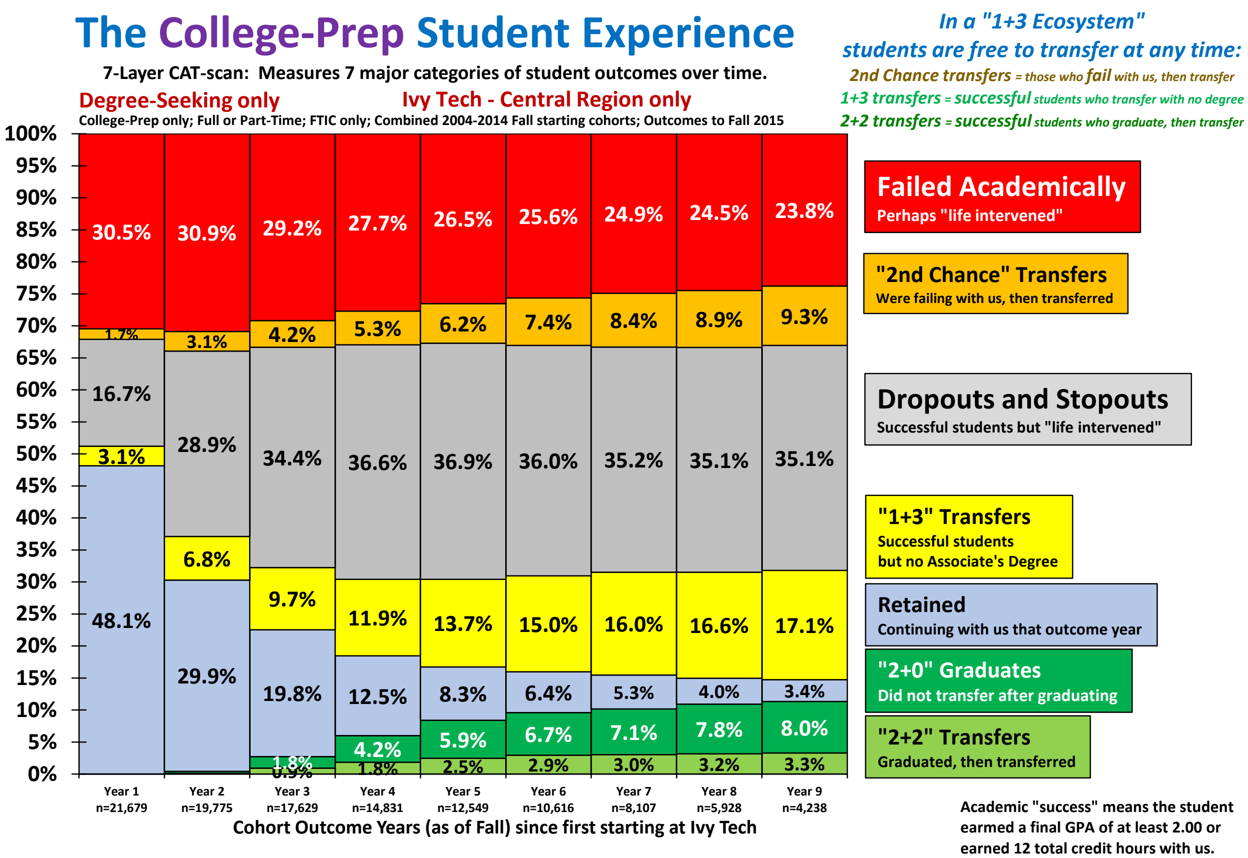
In years past, Florida and Indiana community colleges required placement tests of all their entering students. College-prep students, often referred to as developmental students, are students whose placement test scores show them to not be academically ready for college. They graduated from high school and seek a college degree. They are advised to begin community college by taking remedial courses designed to better prepare them in basic reading, writing, and math before transitioning to college-level coursework.

State laws in Florida and Indiana no longer allow such tests to be required of all community college students. It is now more difficult to research student success, but for the time frame of this study it was possible to split students into the two separate research groups of college-ready and college-prep students.

Using their CAT-scan data mart, Ivy Tech outcomes were easily split between college-prep and college-ready students (see Figure 4). Internal graduation rates were computed over an 8-year horizon for a combination of part-time and full-time first-time-in-college degree-seeking students.

Figure 4. College-prep and college-ready students have different experiences.





College-ready students at Ivy Tech had more than twice the graduation rate (25.3% = 21.6% + 3.7%) as college-prep students (11.0% = 7.8% + 3.2%).

Valencia College provides an interactive tool on their public website (Valencia College, 2018) that allows 8-year graduation rates to be reported the same way that Ivy Tech reported theirs. College-ready students at Valencia had almost twice the graduation rate (48.9%) as college-prep students (27.0%).

In both colleges the data show that being college-ready is strongly associated with higher graduation rates, with roughly twice the rate.

The experiences of nongraduating students are also worth analyzing and improving. College-ready students experience college in much different patterns over time than college-prep students. Ivy Tech CAT-scans invite consideration of many alternative outcomes including retention, 1+3 transfers, drop-outs, second-chance transfers, and failed students (see Figure 4).

Researchers sometimes recommend a combined success metric to include graduates plus transfers. The Institute for Higher Education Policy (Janice & Voight, 2016) recommended limiting transfers to programs that are longer than the previous program, and did not distinguish between 1+3 transfers and second-chance transfers. Regardless of the transfer definition used, adding transfers to graduation rates may prove useful in narrowing performance gaps across ecosystems.

Figure 4 illustrates what happens when adding 1+3 transfers (yellow areas) to graduates (green areas). After 8 years Ivy Tech college-ready students show a 1+3 transfer–adjusted completion rate of 46% compared to college-prep students at 28%.

Scorekeeping analytics are often the criteria used to evaluate the results from research studies designed to improve student success. When all transfers are scored as failures, and when student aptitude mix is not considered, research studies can lead to inconclusive results or even incorrect results. Better scorekeeping could lead to more-accurate research studies.

Regardless of the scorekeeping formula used, the student experience and completion success rates vary widely as a function of college readiness. These are not identical populations where the mix of students of each type has no effect on completion rate scorekeeping.

RESEARCH QUESTION 3: HOW DOES AN ECOSYSTEM AFFECT TRANSFER BEHAVIOR AND STUDENT MIX?

University admissions practices determine the local community college ecosystem.

Given high rates of transfer, and corresponding low rates of graduation, it is an all-too-common mistake to think that 1+3 colleges are to blame for choosing a 1+3 transfer strategy. External consultants who have closely studied Florida colleges as their role models advise against supporting the transfer goals of students who do not wish to stay until graduation. Without regard to the effects of a transfer-oriented ecosystem, consultants challenge college leadership to communicate to their students in ways to try to create a stronger value proposition for students to complete an associate degree before transfer.

The theory that transfers are something out of place and to be avoided is countered in recent research (Shapiro et al., 2016). That paper concludes, “Multiple-institution attendance is common. Simply recommending to students that they not change institutions and promoting the benefits of single institution attendance does not seem to be useful any longer” (Shapiro et al., 2016, 25).

The 2-year colleges do not control student transfer opportunities. Rather, it is the admission practices of the 4-year universities that determine whether community colleges operate within a 1+3 or 2+2 ecosystem. When given a choice, many students will transfer early in order to spend more time at the school at which they plan to earn their bachelor’s degree. Community colleges do not get to choose their ecosystem as a strategy. The only choice college leadership gets to make is how much to advise students on their transfer choices and what courses to advise students to take before they leave.

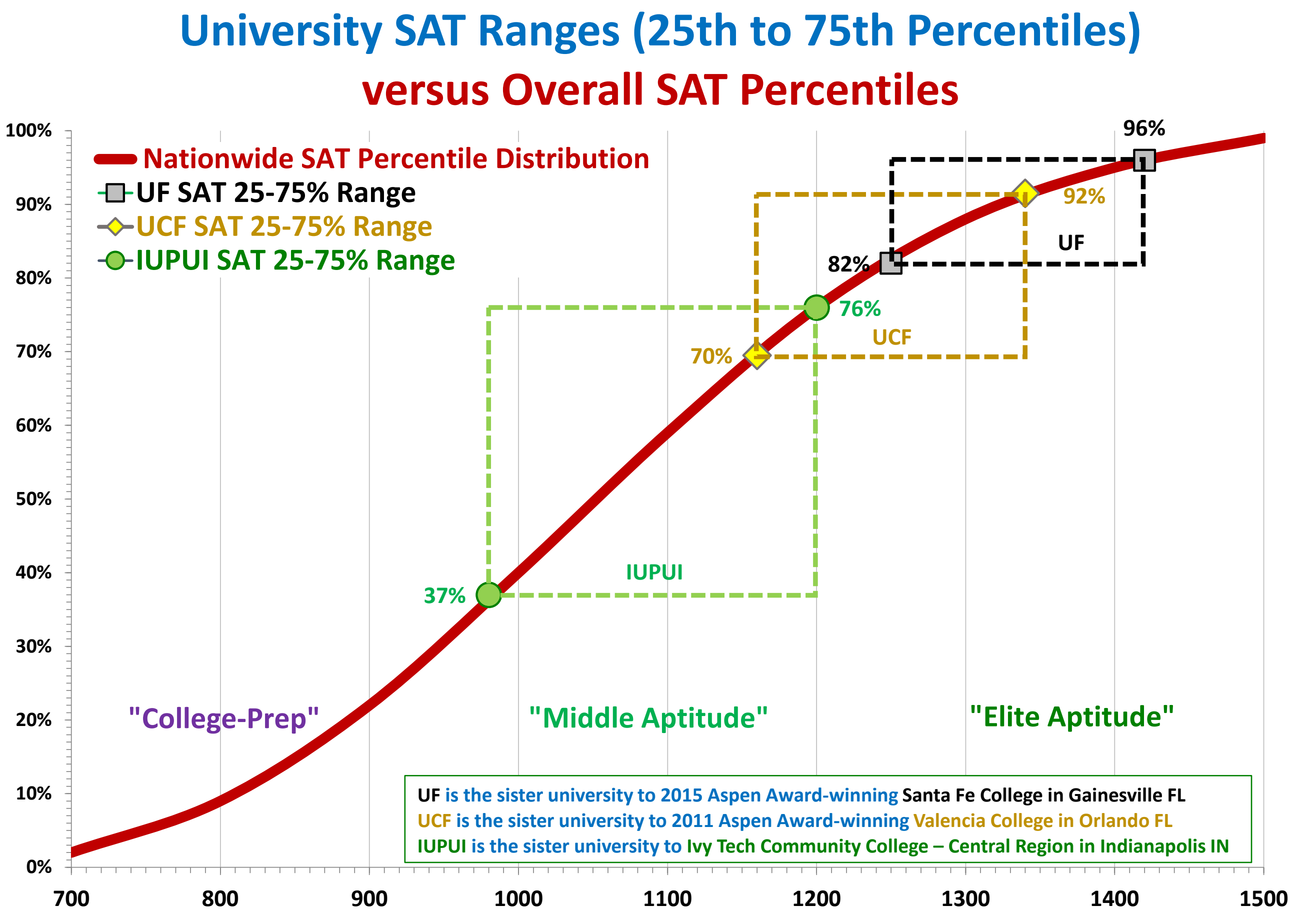
Ecosystems behave much differently when the sophomore year choice is open for individual students to decide for themselves. Most programs at IUPUI require only 28 college credits earned before students can be admitted as transfers, and some programs require only 24. In Ivy Tech 90% of all transfers-out are *before* graduation, and over 70% of all transfers-out to IUPUI are before graduation. In Valencia College, the pattern is reversed, and 86% of all transfers-out from Valencia to UCF are *after* graduation (UCF Institutional Knowledge Management [IKM], 2011–15).

The pairing between the local community college with its nearby sister public university greatly influences the student mix in terms of student aptitude and college readiness, especially in isolated communities. When the local sister university admits only the best-qualified students, the aptitude mix of local community college students must correspondingly increase to fill the educational gap.

Many students are place bound and have a limited choice as to where they can go to college. Education deserts are places where there is no local option available for a place-bound student to attend a college of the right fit (Hillman & Weichman, 2016). Capacity constraints and the admissions practices for a sister university can effectively create a local education desert for students who do not meet academic standards. In 2+2 environments, capacity constraints can cause many excellent college-ready but place-bound students to begin at a community college. These students could have started at the local university if they resided in a different ecosystem.

Figure 5 shows how the range of freshman SAT scores vary across three universities. The red curve shows the cumulative distribution of nationwide SAT percentiles (College Board, 2017). Ranges of freshman admission 25th to 75th percentiles are shown as boxes on this curve (Prep Scholar, 2018).

Figure 5. Admissions standards vary widely for the local sister universities of community colleges.



Comparing the 25th to 75th percentile SAT scores for freshman admissions, UCF (70%–92%) has a much better-prepared mix of entering students than IUPUI (37%–76%). The University of Florida (UF) (82%–96%) has an even better-prepared mix of students than UCF. UCF is the sister university to 2011 Aspen Prize–winning Valencia College in Orlando, Florida, while UF is the sister university to the 2015 Aspen champion, Santa Fe College in Gainesville, Florida.

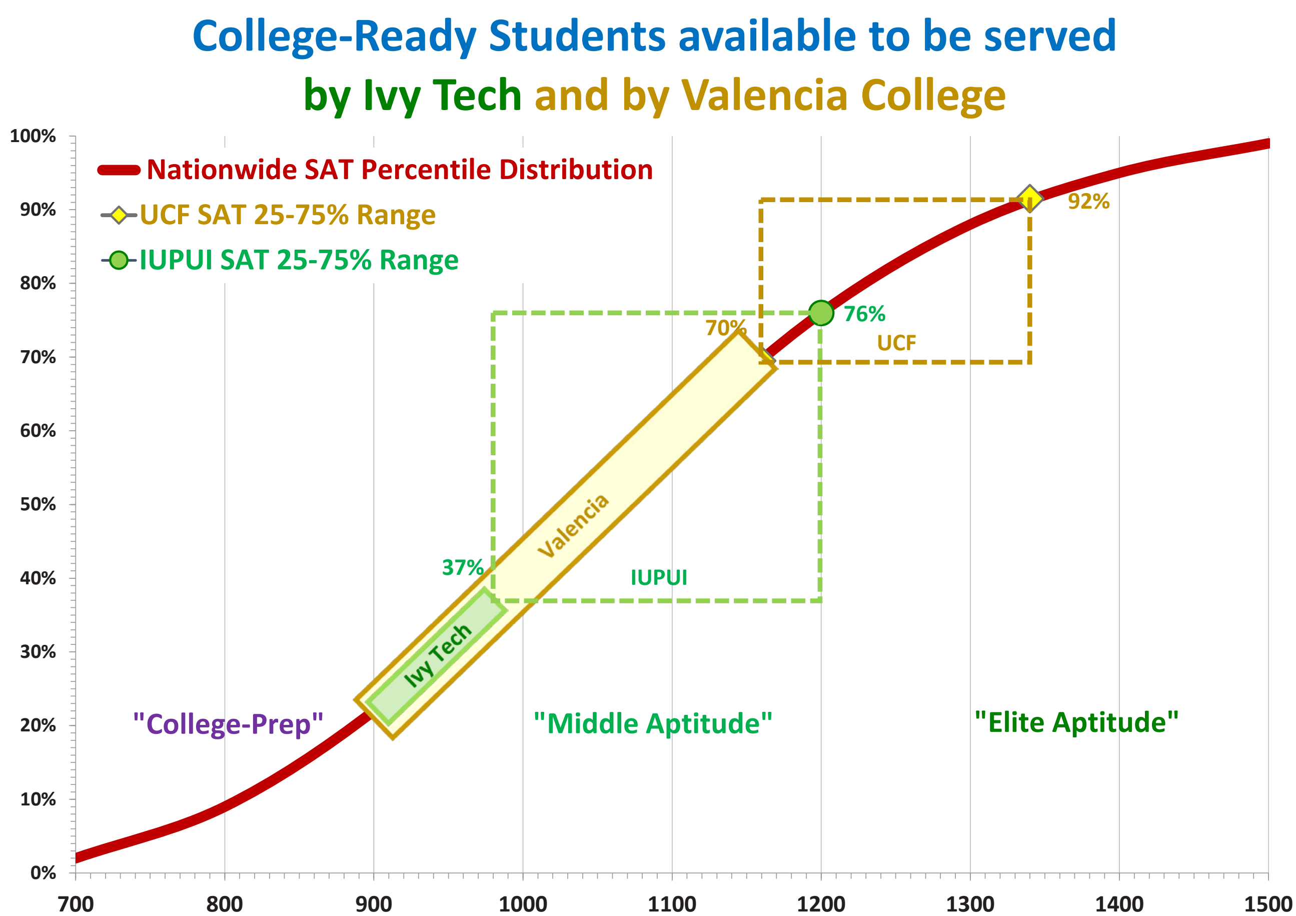
The 25th to 75th percentile range of SAT scores barely overlap between IUPUI and UCF. Some of the top half of students at IUPUI would only rank within the lower quartile of UCF's freshman class.

Nevertheless, these schools appropriately serve their role within their educational ecosystem. Given UCF's size and capacity constraints, they cannot grow larger, so they must turn away more and more freshman applicants. Fortunately, these students can attend Valencia College (and other local community colleges) where they are guaranteed a direct-connect admission to UCF on graduation.

Community colleges also serve many elite aptitude students, and offer honors programs to target these students. Universities compete aggressively for the best-prepared students and are less likely to compete for those students who fall below their 25th percentile—especially when the university is capacity constrained. Students who are not admitted to their local public university can instead attend their local community college.

Based on the 25th percentile of sister university SAT scores, the aptitude mix of college-ready students available for Valencia College to serve (below 70th percentile) is a much wider range of middle aptitude students than those left available to Ivy Tech (below 37th percentile) (see Figure 6). Consequently, the Valencia college-ready student mix is wider and shifted to the right on the horizontal SAT scale compared to Ivy Tech. For college-prep students, a right-shift effect is less certain, but could still occur because IUPUI's lower quartile of students can more easily dip into the college-prep market.

Figure 6. The college-ready students who enroll at Valencia should be shifted to the right of Ivy Tech's college-ready mix.



These data show how the mix of students starting college at Valencia should be much better prepared to succeed than those starting college at Ivy Tech. This does not mean that either college should try to change the mix of students they serve, but it does mean that scorekeepers need to work harder at completion scorekeeping to control for mix effects.

RESEARCH QUESTION 4: CAN WE IMPROVE OUR UNDERSTANDING OF COLLEGE READINESS BEYOND JUST A READY-OR-NOT SPLIT?

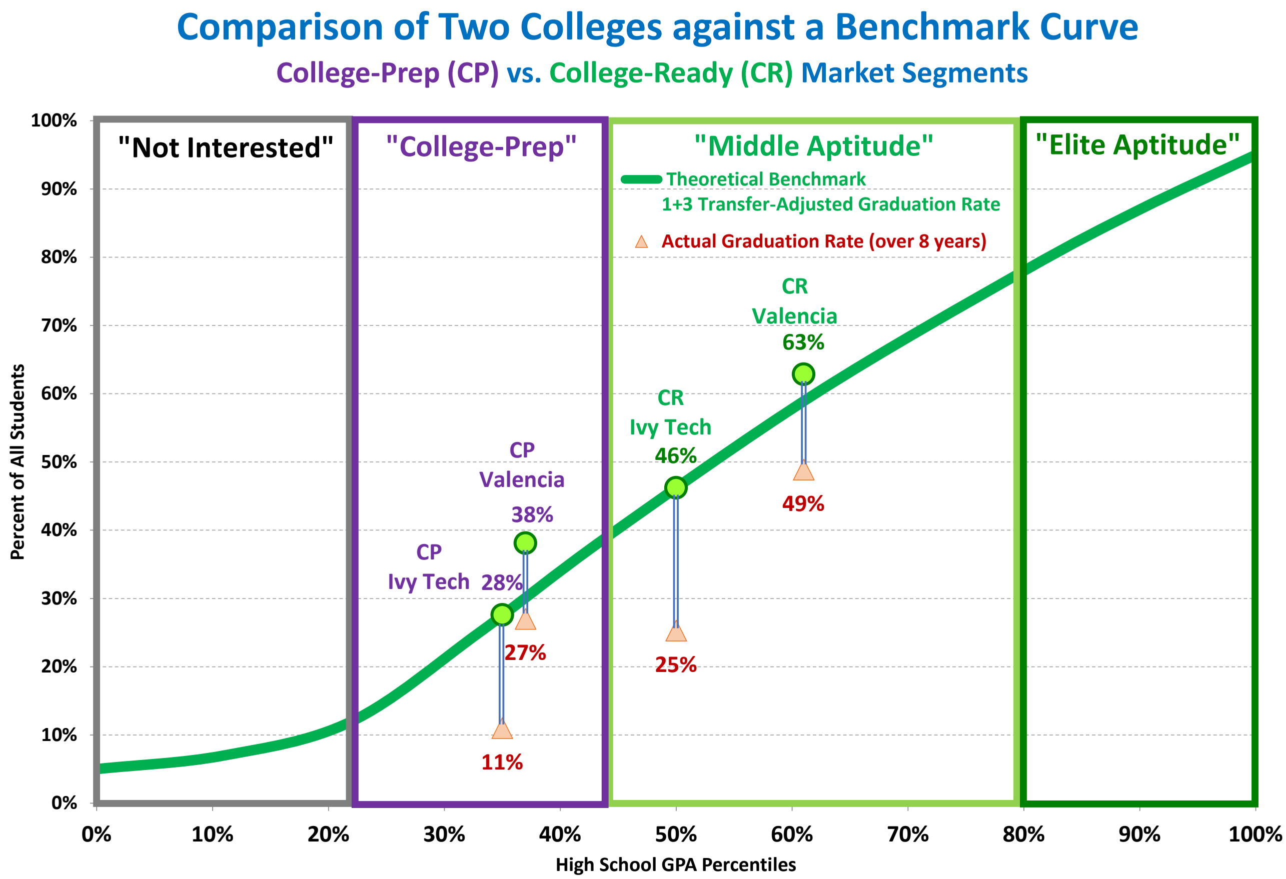
The use of placement tests to flag community college students as being ready (or not ready) for college-level coursework is a small step toward understanding and advising students of diverse backgrounds. Young adults enrolling in college resent being categorized as not yet ready, and there are better ways to evaluate student readiness to succeed.

Colleges and universities with admissions standards often require standardized aptitude or achievement tests to guide their choice of student applicants to accept. High school GPAs and percentiles are also widely used in the admissions process.

It seems logical that students who do well in high school will be better prepared to succeed in college. An in-depth study (Balfanz et al., 2016) confirms that students who graduate from high school with higher GPAs are much more likely to succeed in college. The Balfanz study also found that high school GPA is a better predictor of college success than aptitude tests alone. Using GPA as an indicator of college readiness is useful because aptitude and placement tests are not available for all college students, but all students have a high school GPA.

In theory, college completion success rates could be modeled to show a steady increase as a function of whatever student aptitude measurement scale is used (test scores, GPA, or any logical combination). The green curve in Figure 7 is an illustration of what such a curve might look like. The horizontal axis is defined to be high school GPA percentiles (although it could be any other aptitude scale). The vertical scale is modeled as the percent of students likely to succeed in college. For Ivy Tech and Valencia colleges, the 1+3 transfer–adjusted graduation rate is plotted against this scale, and split between college-prep (CP) and college-ready (CR) students.

Figure 7. In theory, 1+3 transfer-adjusted graduation rates could be plotted against a national benchmark curve.



It is not known whether curves like this are available from any published source. Therefore, the exact shape of this green curve is only an educated guess. To aid in modeling this curve, data on student aptitude and success rates are parameterized against four market segments.

Elite universities have graduation rates that come close to the high graduation rates shown for the elite-aptitude student segment. Middle-aptitude and college-prep students split the middle part of the graph. Students labeled as "not interested" in college are the least likely to succeed.

The Balfanz study (Balfanz et al., 2016) provides data that help to define the widths of the four student market segments illustrated in Figure 7. Twenty-two percent of students did not attend college within 10 years of high school graduation (the not-interested market segment). Another 22% of high school graduates do enroll in college but are not strongly prepared and are at risk of failing (the college-prep market segment). The rest are college-ready and are further split between the top 20% (the elite-aptitude market segment) and everyone else in the middle (the middle-aptitude market segment).

More research is needed, but this proposed curve is useful to illustrate important concepts. The shape of this green curve was intentionally designed to fit the data available when comparing 1+3 transfer–adjusted graduation rates across Valencia and

Ivy Tech colleges. Neither college had high school GPA data on a student-by-student basis, but their placement test split for college readiness allows two groups of students to be considered for each college.

On the horizontal axis, the college-prep and college-ready splits for each school are placed separately within their horizontal market segments. The exact horizontal percentile placement for these schools is unknown, but the relative market positioning to their sister universities suggests that Valencia is shifted to the right of Ivy Tech, especially for college-ready students.

On the vertical axis, each college's 8-year actual graduation rates are shown as red triangles. The green circles are meant to show the student's completion perspective in terms of a 1+3 transfer–adjusted graduation rate. The 1+3 transfer rates are not available for Valencia College, but their ecosystem discourages transfers. For the sake of illustration, a rough estimate would be two-thirds of the Ivy Tech rates.

There are a lot of unknowns in Figure 7, but it does illustrate what could be studied if enough data were gathered along a national benchmark curve for 1+3 transfer–adjusted graduation rates. Some important things to look for when comparing colleges across diverse ecosystems are the following:

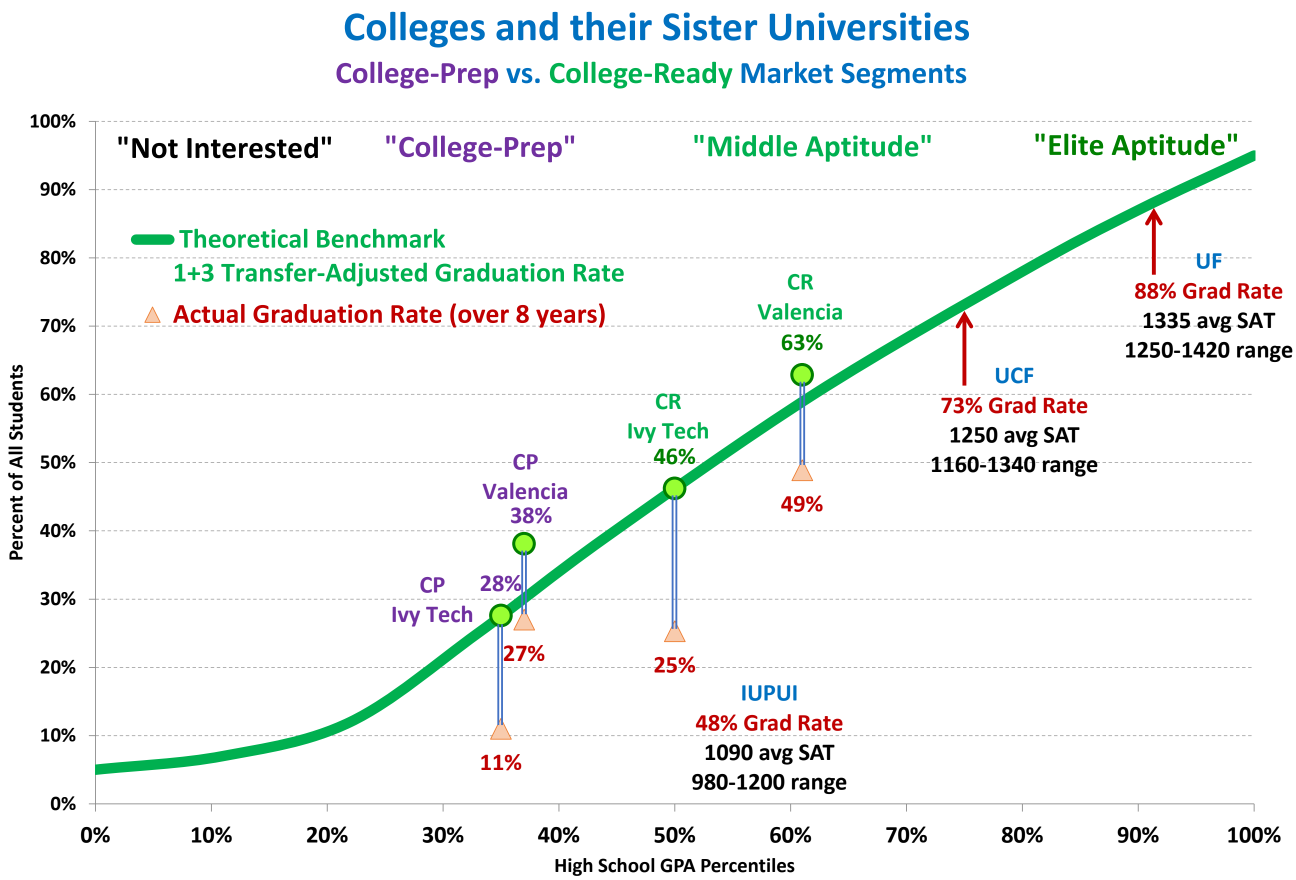
1| A comparison of college-prep against college-ready students should reveal major differences in graduation rates, transfer rates, and transfer-adjusted rates. These performance differences should be heavily influenced by differing levels of college readiness.

2| Low graduation rates for a college (such as Ivy Tech) might be explainable based on the mix of students served and the transfer-rates expected within its ecosystem.

3| High graduation rate performance for a college (such as Valencia) would be further validated by showing transfer-adjusted graduation rates raised above a national benchmark curve.

Figure 8 adds additional data to illustrate the relative positioning of three sister universities along a student aptitude benchmark curve. The exact shape of this curve and exact placement of colleges and universities on this graph is not currently known but could be calculated at the state level by authorities with access to both high school GPAs and college student outcome records.

Figure 8. A national benchmark curve would allow the performance of community colleges to be compared to their sister universities.



UCF and UF are placed to the right on this graph based on their freshman SAT quartiles (Prep Scholar, 2018). UCF and UF have relatively high graduation rates (College Navigator, 2018). There is no public source for 1+3 style transfer rates. As premier schools, UCF and UF transfer-out rates may be mostly second-chance transfers. Assuming their 1+3 style transfer rate is low, we use their graduation rates alone to compare to the green benchmark curve.

It is harder to place IUPUI on this curve. They have a high rate (31%) of reported total transfers out (College Navigator, 2018). These transfers will include both second-chance transfers and 1+3 style transfers including students using this regional campus as a transfer stepping-stone to Indiana University or Purdue University main campuses. IUPUI's freshman SAT quartiles place it somewhere just above the middle on the student aptitude horizontal scale. It seems likely that IUPUI's 1+3 transfer-adjusted graduation rate would fall very close to where it would be expected on the green curve.

Differences in completion performance across all colleges and universities could be better interpreted using a national benchmark curve based on a student aptitude scale.

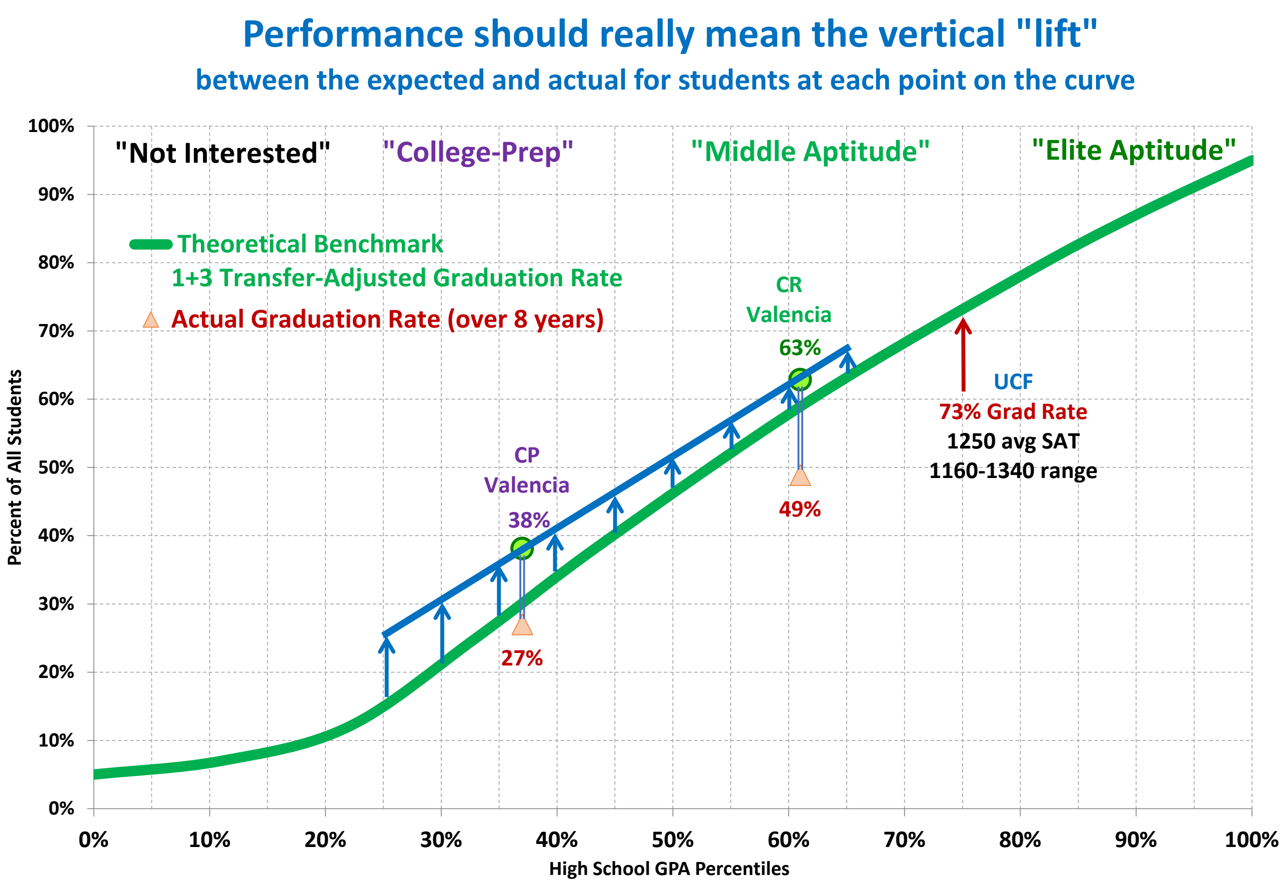
RESEARCH QUESTION 5: HOW DO YOU SHOW PERFORMANCE IMPROVEMENT WHEN THERE ARE DIFFERENCES IN STUDENT MIX?

Performance means a vertical lift in student success, not a right shift in student mix.

When modeling performance against a student aptitude scale, performance gaps across groups of students can be narrowed and more carefully interpreted. Any vertical movement upward is progress and any performance above the benchmark curve is worthy of recognition.

Figure 9 illustrates how vertical lift could someday be reported as a continuum against a benchmark curve, and not just as two data points for the average success rate split between college-prep and college-ready students. An ideal approach might be to report success at 5-percentile increments along the horizontal axis. (The blue line is not real data for any college but demonstrates what a line might look like for a college like Valencia.)

Figure 9. Vertical lift is the value added to success that the college offers a student.



It is possible, as shown here, that a college's performance lift with students could vary along the horizontal axis. In this theoretical scenario, the college provides greater vertical lift in success for those students who come to college less well prepared.

For students trying to decide where to attend college, an advisor could use graphs like these to coach a student based on where that individual student sits on the horizontal axis. This is much better information than just the average graduation rate for a college or university.

RECOMMENDATIONS FOR FUTURE RESEARCH

More research is needed to validate the findings of this study. Many more community colleges and their sister universities need to be analyzed across a broad range of ecosystems.

This paper hypothesizes that high school GPAs and their percentiles might guide the interpretation of student performance, but necessary testing has not yet been done. Neither Valencia College nor Ivy Tech had high school GPA data available to use on a student-by-student basis. Privacy laws make it difficult to access these data, so testing their use may need to be conducted on a state or national level.

When studies like this one are done in the future, researchers might consider exploring the following research questions:

WHAT IS THE BEST WAY TO MEASURE VERTICAL LIFT WHILE CONTROLLING FOR HORIZONTAL SHIFT?

A college's performance should be judged by the vertical lift its students exhibit compared to a benchmark curve, not the right shift that occurs when one college is able to recruit a better mix of students. This is true not only of community colleges but also of 4-year schools. Middle-aptitude-serving universities cannot be expected to have graduation rates as high as the elite-aptitude-serving universities. Any college or university could have its students stratified along a high school GPA scale so as not to judge a whole college on a single number that presumes all students are equally well prepared to succeed.

HOW USEFUL ARE 1+3 TRANSFER–ADJUSTED GRADUATION RATES?

Using a 1+3 transfer–adjusted graduation rate represents the student perspective on transfers as a positive outcome, but this metric may prove to have its own limitations. Perhaps a better scorekeeping formula would add in student retention and not just transfers. Can ecosystems be classified, and separate benchmarks developed for each type of environment? More research is needed on how different scorekeeping formulas perform when measured across diverse ecosystems. The important thing is to test those formulas against a horizontal scale that allows students to be differentiated based on their readiness to succeed.

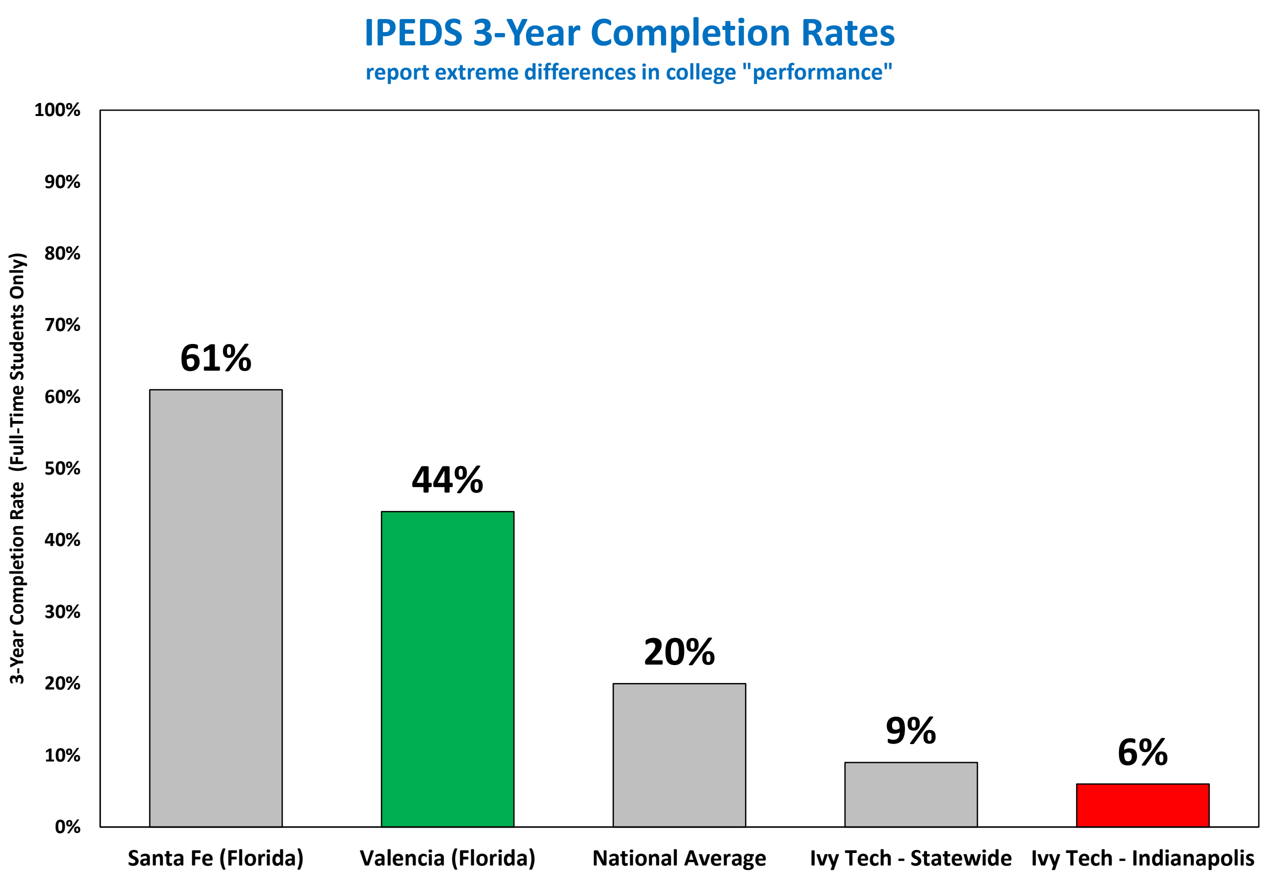
CAN WE BUILD BETTER DECISION-SUPPORT TOOLS FOR USE BY STUDENTS AND THEIR ADVISORS?

When students are advised in their college choices, they should be given information tailored to their level of college readiness, and not just a single performance rate for the average student at a college. Students have a range of outcomes that they might experience over time, as shown by CAT-scan graphs. Perhaps someday an online tool could be provided to students that asks them for their high school GPA and a particular college they would like to consider. The system could then respond with a CAT-scan-style 7-layer range of outcomes (adding up to 100%) that students with GPAs like them experience at that college by the end of 8 years. The student does not need a performance score for the college, but would be better advised to consider all the possible outcomes that can and do happen for similar students.

CAN WE IMPROVE THE CONVERSATION ABOUT BEST PRACTICES AND IMPROVEMENT OPPORTUNITIES?

Researchers, benchmarking organizations, and consultants to colleges are continually seeking to discover those best practice initiatives in use at high-performing colleges that all colleges should consider adopting. Unfortunately, they are misinformed by triple-digit gaps in completion analytics as reported by scorekeepers in the past. Combining many small benefits from best practices in classroom learning success, it seems plausible to achieve a 5% to 10% improvement in overall completion rate. Best-practice student initiatives cannot cause a ten-fold improvement as traditional IPEDS-style 3-year scorekeeping implies. Figure 10 shows how benchmarking and scorekeeping is typically done (National Center for Education Statistics, 2015). IPEDS-style graduation rates like these differ to such an extreme that the results lack face validity.

Figure 10. Single performance scores for a college leave so much unexplained.



AUTHOR’S BACKGROUND AND RESEARCH BIAS

Before serving as IR director at Ivy Tech, I had the privilege to serve in the same role at Valencia College. This meant that I first worked at one of the nation’s most prestigious community colleges with high rates of academic success. I suddenly found myself working at a college where we had inexplicably low completion rates according to IPEDS rules.

I arrived at Ivy Tech believing that transfers before graduation should never be thought of as a success for a college. By the time I left, I had completely reversed my thinking. Students in both Indiana and Florida were making the right choices for themselves given the options available to them. If a successful student earns the opportunity to transfer to a better-funded college, especially if their goal is to earn their 4-year degree at that specific school, that is the choice I would make (or would want my child to make).

Both Ivy Tech and Valencia naturally serve the role they need to play within their ecosystems. Neither the colleges nor their ecosystems need fixing. The mix of students these colleges serve also does not need fixing. It is the scorekeeping that is broken, and everyone needs to work much harder at doing completion analytics better. It should be possible to improve our research, benchmarking, and advising through a deeper understanding of how diverse students experience college differently across diverse ecosystems.

REFERENCES

Balfanz, R., DePaoli, J. L., Ingram, E. S., Bridgeland, J. M., & Fox, J. H., (2016). *Closing the college gap: A roadmap to postsecondary readiness and attainment.* Civic Enterprises, Everyone Graduates Center at the School of Education at Johns Hopkins University, Baltimore, MD.

College Board. (2017). *Total and section score user group percentile ranks by gender and race/ethnicity.* Accessed May 2, 2018, at https://collegereadiness.collegeboard.org/pdf/sat-percentile-ranks-gender-race-ethnicity.pdf.

College Navigator. (2018). *Overall graduation rate and transfer out rate.* Accessed May 2, 2018, at https://nces.ed.gov/collegenavigator/?q=iupui&s=IN&ct=1&id=151111#retgrad, https://nces.ed.gov/collegenavigator/?q=ucf&s=FL&ct=1&id=132903#retgrad, https://nces.ed.gov/collegenavigator/?q=university+of+florida&s=FL&ct=1&id=134130#retgrad.

Cornett, J., & Hancock, S. (2015). *"CAT-scan" graphs to dissect all student outcomes over all periods of time* [Conference presentation]. Association for Institutional Research Annual Forum, Denver, CO, May 27, 2015.

Cornett, J., Childress, J., & Roe, R. (2016). *Measuring and evaluating "1+3" transfer success from the student point of view* [Conference presentation]. Indiana Association for Institutional Research Annual Conference, Indianapolis, IN, April 7, 2016.

Hillman, N., & Weichman, T. (2016). *Education deserts: The continued significance of "place" in the twenty-first century.* Viewpoints: Voices from the Field. American Council on Education, Washington, DC.

Janice, A., & Voight, M. (2016). *Toward convergence: A technical guide for the postsecondary metrics framework.* Institute for Higher Education Policy, Washington, DC. Accessed May 5, 2018, at http://www.ihep.org/sites/default/files/uploads/postsecdata/docs/resources/ihep_toward_convergence_low_2b.pdf.

National Center for Education Statistics (NCES). (2015). *IPEDS data feedback report 2015.* Accessed April 18, 2016, at http://nces.ed.gov/ipeds/DataCenter/DfrFiles/IPEDSDFR2015_151111.pdf.

National Center for Education Statistics (NCES). (2020). *IPEDS Integrated Postsecondary Education Data System: Use the data.* Accessed February 26, 2020, at https://nces.ed.gov/ipeds/use-the-data.

National Student Clearinghouse. (2005–15). *About the clearinghouse.* Accessed February 26, 2020, at https://www.studentclearinghouse.org/about/.

Prep Scholar. (2018). *SAT score analysis (New 1600 SAT).* Accessed May 2, 2018, at http://www.prepscholar.com/sat/s/colleges/IUPUI-admission-requirements, http://www.prepscholar.com/sat/s/colleges/UCF-admission-requirements, http://www.prepscholar.com/sat/s/colleges/University-of-Florida-admission-requirements.

Shapiro, D., Dundar, A., Wakhungu, P.K., Yuan, X., Nathan, A, & Hwang, Y. (2016, September). *Time to degree: A national view of the time enrolled and elapsed for associate and bachelor's degree earners (Signature Report No. 11).* National Student Clearinghouse Research Center, Herndon, VA.

Shugart, S. (2013, February 7). *Rethinking the completion agenda.* Inside Higher Ed. Accessed May 5, 2018, at https://www.insidehighered.com/views/2013/02/07/moving-needle-college-completion-thoughtfully-essay#ixzz2KEDUZM3w.

University of Central Florida (UCF) Institutional Knowledge Management (IKM). (2011–15). *University of Central Florida Factbook: Fall new undergraduate transfer student enrollment report (Fall 2011–15).* Accessed October 19, 2020, at https://stars.library.ucf.edu/ikm/.

Valencia College. (2018). *8-year cumulative completion rates for FTIC [first-time-in-college] degree-seeking students for the 2005 cohort.* Student indicators–Completion Over Time [Interactive Tableau report] Accessed May 23, 2018, at https://valenciacollege.edu/academics/analytics-and-planning/analytics-and-reporting/reporting/strategic-indicators/student-indicators.php.

Brain Drain in Maryland: Exploring Student Movement from High School to Postsecondary Education and the Workforce

Amber Bloomfield, Bess A. Rose, Alison M. Preston, and Angela K. Henneberger

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Abstract

Brain drain—the movement of high school and college graduates out of state for employment—is a concern for state policymakers. This study focuses on brain drain of students who graduate from high school in Maryland. Using data from the Maryland Longitudinal Data System and applying propensity score matching to control for differences between the groups, we evaluated the degree to which brain drain exists in Maryland, and which students are likely to contribute to brain drain. Findings indicate that brain drain does exist in this state: students who graduated from a Maryland high school and who attended college out of state were less likely to return to Maryland to join the workforce compared to students who remained in state for college. Additionally, higher-achieving students were more likely to be lost to brain drain.

Keywords: brain drain, propensity score matching, student migration

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INTRODUCTION

States invest significant funds in public school systems in an effort to support students and prepare them for success. One of the direct returns on the investment in public education would take the form of in-state workforce participation (Winters, 2015). Researchers call the loss of in-state high school and college graduates to other states brain drain, and it is a concern for state policymakers (Kelchan & Webber, 2018; Zhang & Ness, 2010). Recently, many states have invested in state-wide merit scholarship programs designed to encourage students who have strong potential to graduate from a state higher education institution and so ultimately bolster the state's educated workforce (Zhang & Ness, 2010).

Brain drain can occur at two transition points—in-state high school students can be lost to out-of-state colleges or in-state college students can be lost to the out-of-state workforce. To understand the big picture of the brain drain phenomenon, it is important to consider student migration (i.e., movement of students out of their state of residence) at both transition points, and to follow students from high school through college and then into the workforce. However, prior research that takes this approach is limited.

In this study, we used data from the Maryland Longitudinal Data System (MLDS) to examine the movement of Maryland public high school graduates to college and then to the Maryland workforce. First, we examined the student characteristics that were associated with selection into a Maryland college compared to an out-of-state college. Second, we used propensity score matching to examine the role of out-of-state college attendance on the likelihood to return to Maryland for the workforce. Third, we examined the student characteristics of out-of-state college graduates who did return to Maryland for the workforce to identify the type of student who is most likely to be lost to brain drain.

A clear understanding of the migration patterns of students and the motivations behind student migration is important for researchers, policymakers, and other stakeholders to develop and implement programs designed to encourage student retention and eventual workforce participation. Students who attend college can decide to stay in their state of residence or attend college in another state, and their decision may rest on a variety of factors such as cost, institutional characteristics, and future employment prospects (Zhang & Ness, 2010). It is generally expected that students will examine the options and make selections according to rational choice theory, which contends that people arrive at a decision by examining all the options then selecting the option that best allows goal attainment according to a set of criteria (Finn & Darmody, 2017). An understanding of student mobility patterns can help researchers determine the criteria commonly associated with students' college attendance decisions, and policymakers can use these criteria to implement programs or policies designed to increase the ability for in-state institutions to meet those criteria.

Human capital theory also asserts that people make important life decisions, such as the decision of whether to attend college and, if so, which college to attend, by examining the options and selecting the one best suited for obtaining the goal in mind. In this case, the goal is always the increase of the individual's human capital (i.e., abilities, education, and training) in order to improve the individual's outcome in the labor market (Heller & Rasmussen, 2002). Students will choose to educate themselves where they can find the best balance of cost and credentialing in order to build their human capital to enter the workforce in a position with the highest benefit, regardless of geography. From this human capital perspective, state policymakers are also interested in how individuals improve themselves for the job market through education. It follows logically that if a state spends public funds to support an education or training program for a student, the state wants that student to enter that particular workforce and generate income that returns to the state at the highest rate possible. Students who are educated using public funds and who then leave the state for college or employment can be viewed as losses of state resources.

RELATED LITERATURE AND HYPOTHESES

Brain Drain from High School to College

The first major transition point for a college-bound student involves the decision of where to attend college. There are many considerations involved, and choosing to go to an out-of-state college is a function of the available institutional opportunities and geographic characteristics of both the original state and the destination state (Cooke & Boyle, 2011). States with the highest rates of brain drain between high school and college are smaller states that are densely populated, such as Maryland, or larger states that are densely populated, like Illinois (Cooke & Boyle, 2011). States that are less densely populated, such as Pennsylvania and Indiana, tend to attract students at higher rates, potentially due to their proximity to high-density states (Cooke & Boyle, 2011). The variation in states in terms of geographic size, population, and number and quality of higher education institutions means that considering student migration state by state provides a more accurate picture of the brain drain phenomenon than would a nationwide estimate alone. Eleven states reported a net loss of first-time degree- or certificate-seeking students at 4-year degree-granting public institutions in 2014 (U.S. Department of Education, 2015).

Brain Drain from College to the Workforce

Following college, students seeking employment can either join the workforce in the same state as their college or move to a different state for work. Kodrzycki (2001) reported that approximately 30% of college graduates in the National Longitudinal Survey of Youth relocate to a different state within 5 years of graduation. A more recent analysis using LinkedIn alumni profiles found that 58% of 4-year college attendees had relocated to a different metropolitan area than that of their college (Rothwell, 2015). States that tend to have larger student loss rates either have large rural areas, such as Iowa, or border large cities in other states, as is the case with Delaware's proximity to Philadelphia (Kelchan & Webber, 2018). Overall, states in the South and the West are more likely to see gains from student migration while states in the Northeast and Midwest are more likely to see losses (Kelchan & Webber, 2018).

Relocation decisions are influenced by personal characteristics as well as by state economies, population, amenities, and whether the student has a history of moving across state lines as a child (Kodrzycki, 2001). Recent nationally representative findings indicated that students who were more likely to leave the state of college attendance had attended highly selective institutions, had applied to multiple institutions, or were grant recipients (Ishitani, 2010). Students who were more likely to stay in the same state after college attendance were more often Hispanic or had attended college in states with a higher gross domestic product (Ishitani, 2010).

Brain Drain from High School to College to the Workforce

The study of brain drain from high school to college to the workforce has been approached using multiple data sets at corresponding points in time (e.g., Groen, 2004), or by using one longitudinal data set that follows a sample of students across both transition points (e.g., Perry, 2001). These studies consistently found that students who attend college in their home state are more likely to work in their home state when compared to those who attend an out-of-state college. Groen (2004) investigated brain drain using two separate longitudinal data sets, both including students who initially enrolled in a 4-year college in the 1970s: the Mellon Foundation's College and Beyond data set (C&B, 1976 cohort) and the National Longitudinal Study of the High School Class of 1972 (NLS-72). Controlling for gender and SAT score, Groen (2004) found that 48% of students in the C&B sample who attended college in their original state of residence versus 39% of students who attended college out of state; comparable percentages in the NLS-72 sample were 62% versus 52%.

Perry (2001), investigating brain drain using data from the NCES Baccalaureate and Beyond Longitudinal Study, found that 83% of in-state graduates lived in their original state of residence, compared to only 52% of out-of-state graduates. Perry also found that the majority of college graduates in her sample had graduated from a college in their original state of residence (i.e., most college graduates were in-state students). In addition, students who attended an in-state college were more likely to live in the state of the college from which they had graduated than were students who attended an out-of-state college (Perry, 2001).

It is important to note that both Groen (2004) and Perry (2001) examined students' state of residence, and not employment status within the state. For the purpose of studying brain drain, state policymakers would be interested in students' eventual contribution to the workforce and ability to support the economy of the state, not just where they reside. Much of the research that does address employment outcomes centers on the results of state-sponsored scholarship programs intended to encourage students to stay in state for college (e.g., Harrington et al., 2016; Hawley & Rork, 2013; Hickman, 2009; Sjoquist & Winters, 2013), rather than providing the general overview of student migration necessary to fully understand the trends. The current literature generally focuses on either the transition from high school to college, or the transition from college to workforce, possibly due to the difficulty of obtaining linked longitudinal data over time. While some research has been able to longitudinally investigate the full path of brain drain, these studies are limited by considering only college graduates (Perry, 2001), or examining employment location after a considerable time gap (Groen, 2004). A further limitation of prior research has been the lack of sufficiently rigorous approaches to control for preexisting differences between students who enrolled in state and those who enrolled out of state (e.g., SAT scores, marital status). Those studies that were able to track students from high school through college and into the workforce had limited information about these students and so could not control for potential differences between those who chose an out-of-state institution and those who chose an in-state institution. Groen (2004) investigated the role of SAT scores in brain drain patterns, but did not investigate other likely relevant characteristics such as race or socioeconomic status. Perry (2001) did not take into account student characteristics when examining brain drain patterns. This gap is of concern because the same factors that may lead a student to select an in-state institution might also affect their likelihood of attaining work in their home state. We address these limitations by investigating the relationship between location of the higher education institution (out of state versus in state) and the likelihood that students return to their home state's workforce, taking into account differences in demographic, academic achievement, and high school characteristics.

The Current Study

In Maryland there is evidence of notable student migration between high school and college as well as between college and the workforce. In 2014 Maryland reported a net loss of 8,881 students between high school and college, the fifth-largest net loss in the country (U.S. Department of Education, 2015). For the second transition point, from college to the workforce, data from the Integrated Public Use Microdata Series (IPUMS-USA) indicated that Maryland had a net migration rate for college graduates under age 40 of approximately 1% from 2000 to 2015 (Bui, 2016). This means that there was an approximately 1% positive difference in the number of college graduates under age 40 who moved to Maryland compared to the number who left. While this particular study indicated a positive net migration rate, there is still a considerable amount of flow in and out of Maryland in the time frame included.

Our study aims to address the limitations of prior research by applying a propensity score matching analysis approach to a unique longitudinal high school–college–workforce extant data set to analyze brain drain at both transition points in Maryland. Data from the MLDS link high school, college, and workforce records across multiple years for Maryland public high school attendees. Thus, this study can examine the same group of students at both transition points. This study answers the following research questions:

1| Do Maryland public high school graduates who enroll in out-of-state colleges differ from those who enroll in in-state colleges with regard to achievement or demographic variables?

2| Does the location of college enrollment change the likelihood of working in Maryland (i.e., is there brain drain in Maryland)?

3| Do students who enroll in out-of-state colleges and go on to work in Maryland differ from students who enroll in out-of-state colleges and do not go on to work in Maryland, or, put another way, who is lost to brain drain in Maryland?

METHOD

The data used for these analyses are from the MLDS, which contains linked longitudinal data from multiple sources.[1] The Maryland State Department of Education provides data for public pre-K–12 students and schools. The Maryland Higher Education Commission provides data for Maryland public and private colleges and students. Out-of-state college enrollment and degree information is obtained through the National Student Clearinghouse. The Maryland Department of Labor Licensing and Regulation provides data for employees in the state who work for employers who are subject to Maryland's unemployment tax law. The workforce data do not include information for federal employees, military employees, individuals who are self-employed, or private contractors. The latest workforce data available at the time of these analyses were for fiscal year 2016.[2]

All Maryland public high school students who graduated in academic year 2008–9 were identified.[3] We focused on graduates whose first year of college enrollment occurred in 2010, excluding those who enrolled in college in 2011 or later, to allow 6 years for the completion of undergraduate education within the time span of the available data (through 2017). This 6-year graduation window is considered adequate for reporting and is a widely used metric for reporting undergraduate graduation rates (Engelmyer, 2019). We further focused on those students whose initial enrollment was in a 4-year institution, whether public or private. Finally, to focus on the role of in-state versus out-of-state college undergraduate enrollment in the likelihood of joining the Maryland workforce after undergraduate education, we excluded the data of students who were still enrolled as undergraduates in 2016. Ultimately, we retained data from 29% of the 2009 Maryland high school graduates for these analyses. The group of students included differs in several ways from other 2009 Maryland high school graduates. For instance, the students retained for analyses tended to have stronger academic indicators than students whose data were excluded for one or more reasons. In addition, students retained for analyses were less likely to belong to minority race or ethnic groups. Table 1 shows the demographic and achievement variables for the retained and excluded students.

MEASURES

In-state and out-of-state college enrollment was measured by examining the first record of college enrollment at a 4-year public or private institution. Covariates included demographic variables (e.g., race and gender), academic achievement indicators (SAT scores, high school GPA), and characteristics of the high schools from which the students graduated (e.g., the percentage of students in the school eligible for free and reduced-price meals). Note that students who had Advanced Placement scores must have opted to take the associated Advanced Placement test; students who took an Advanced Placement courses but did not take the test would not have data for Advanced Placement. Due to the small number of students in some race categories, groups were collapsed into underrepresented minorities (URMs) (Black or African American, Hispanic or Latino, American Indian or Alaska Native, Native Hawaiian and Other Pacific Islander, two or more races) and non-URMs (White, Asian). These categories are consistent with the National Institutes of Health (NIH) definition of URM in sciences (NIH n.d.). Workforce participation in Maryland was

1. For more information, visit https://mldscenter.maryland.gov/.

2. For more information, visit http://www.studentclearinghouse.org/.

3. In future references to enrollment and graduation years, we indicate the academic year. For instance, 2009 corresponds to the academic year 2009, which began in the fall of 2008.

Table 1. Demographic and achievement variable values for students whose data were included in the analyses and those whose data were not included

	Data not included	Data included
	(*N* = 41,461)	(*N* = 16,935)
High school program completion: Met requirements for		
Approved career and technology program	13%	2%
Approved USM and occupational program	10%	9%
Approved USM	46%	78%
Noncompleter	2%	< 1%
Other high school completions	28%	11%
Missing	< 1%	< 1%
Gender		
Male	50%	44%
Female	50%	56%
Race		
White	57%	59%
Black	37%	31%
Asian	4%	9%
Native Hawaiian and Other Pacific Islander	< 1%	< 1%
American Indian or Alaska Native	< 1%	< 1%
Two or more races	1%	< 1%
Ethnicity		
Hispanic or Latino	8%	3%
Not Hispanic or Latino	92%	97%
Highest AP test score	*M* = 2.7; *SD* = 1.4	*M* = 3.4; *SD* = 1.4
Highest IB diploma test score	*M* = 26.0; *SD* = 6.4	*M* = 28.4; *SD* = 6.4
Highest IB grade test score	*M* = 12.3; *SD* = 13.7	*M* = 17.30; *SD* = 14.8
Highest IB diploma proficiency	*M* = 3.34; *SD* = 0.9	*M* = 3.55; *SD* = 0.9
Highest IB grade proficiency	*M* = 4.85; *SD* = 1.3	*M* = 5.20; *SD* = 1.2
PSAT verbal	*M* = 41.01; *SD* = 11.0	*M* = 50.94; *SD* = 10.9

PSAT writing	*M* = 40.54; *SD* = 10.8	*M* = 50.58; *SD* = 11.1
PSAT math	*M* = 41.86; *SD* = 11.4	*M* = 52.48; *SD* = 11.8
Took the ACT/SAT	50%	94%
Took at least one IB exam	1%	4%
Took the PSAT	60%	80%
Took at least one AP exam	20%	70%
SAT/ACT math	*M* = 458.3; *SD* = 118.4	*M* = 547.2; *SD* = 117.4
SAT/ACT verbal	*M* = 455.5; *SD* = 111.0	*M* = 537.8; *SD* = 109.4
SAT/ACT writing	*M* = 450.6; *SD* = 108.3	*M* = 536.6; *SD* = 109.8
Met rigorous high school program requirements for		
Foreign language	33%	72%
Math	24%	61%
Science	12%	39%
Advanced technology education	7%	8%
Completed high school with a cumulative GPA ≥3.0	26%	70%

Note: USM = University System of Maryland; AP = Advanced Placement; IB= International Baccalaureate. Students whose data were included in analyses graduated from a Maryland public high school in 2009, enrolled at a 4-year college in 2010, and were not enrolled in any undergraduate program in 2016. Where available, ACT Reading and ACT English scores are summed, then converted into SAT verbal scores.

coded if the student had at least one workforce record that occurred in the fourth fiscal quarter of the same calendar year as their last year of undergraduate college enrollment, or any quarter of a later year. This approach explicitly excluded the summer quarter following the last college enrollment record, which might indicate temporary summer employment prior to enrolling in graduate school or seeking more-permanent employment. Graduate students who did not have any concurrent employment were classified as students who did not seek employment in Maryland following graduation from an undergraduate program.

ANALYSES

Missing Data

Data, particularly achievement indicators like SAT subtest scores, were missing for several of the students in our sample. We applied multiple imputation to use the patterns among existing data in the data set to extrapolate missing data values (Sinharay et al., 2001), creating 20 complete data sets. In conducting imputation, we assumed that high school information, such as the proportion of students eligible for free and reduced-price meals

Table 2. Demographic and achievement characteristics for Maryland public high school graduates who enrolled in 4-year colleges outside of and in Maryland

	Outside of Maryland	In Maryland
	(N = 8,145)	(N = 8,790)
High school program completion: Met requirements for		
Approved career and technology program	2%	2%
Approved USM and occupational program	8%	11%
Approved USM	78%	77%
Noncompleter	< 1%	< 1%
Other high school completions	11%	10%
Missing	< 1%	< 1%
Gender		
Male	43%	45%
Female	57%	55%
Race		
White	63%	55%
Black	30%	33%
Asian	6%	12%
Native Hawaiian and Other Pacific Islander	< 1%	< 1%
American Indian or Alaska Native	< 1%	< 1%
Two or more races	< 1%	< 1%
Hispanic or Latino	3%	4%
Highest AP test score	M = 3.5; SD = 1.4	M = 3.4; SD = 1.4
Highest IB diploma test score	M = 29.7; SD = 6.2	M = 26.9; SD = 6.3
Highest IB grade test score	M = 17.1; SD = 15.5	M = 17.6; SD = 13.8
Highest IB diploma proficiency	M = 3.6; SD = 0.9	M = 3.4; SD = 0.9
Highest IB grade proficiency	M = 5.3; SD = 1.2	M = 5.1; SD = 1.2

PSAT verbal	M = 51.4; SD = 11.3	M = 50.5; SD = 10.5
PSAT writing	M = 51.0; SD = 11.6	M = 50.2; SD = 10.5
PSAT math	M = 52.7; SD = 12.1	M = 52.2; SD = 11.5
Took the ACT/SAT	94%	95%
Took at least one IB exam	4%	3%
Took the PSAT	82%	82%
Took at least one AP exam	70%	68%
SAT/ACT math	M = 552.0; SD = 118.1	M = 542.7; SD = 116.5
SAT/ACT verbal	M = 542.8; SD = 113.7	M = 533.3; SD = 105.1
SAT/ACT writing	M = 542.3; SD = 114.6	M = 531.2; SD = 105.0
Met the rigorous high school program requirements for		
Foreign language	71%	73%
Math	61%	62%
Science	38%	39%
Advanced technology education	8%	8%
Completed high school with a cumulative GPA ≥3.0	69%	71%

Note: USM = University System of Maryland; AP = Advanced Placement; IB= International Baccalaureate. Where available, ACT Reading and ACT English scores are summed, then converted into SAT verbal scores.

at a given high school, was missing at random and conditional on known variables; we also assumed that this information could be reasonably imputed. However, other information, such as SAT scores, could be missing data or might indicate that the student did not take the SAT. To handle this type of missingness, we first generated variables indicating whether a student had taken the PSAT or SAT/ACT. Subtest scores were then imputed only if the indicator variable for that test was positive; if the person did not have a score on any SAT or ACT subtest, no scores were imputed (approximately 6% of the sample).[4] A similar process was followed for scores on the PSAT subtests (approximately 18% of students were missing all PSAT subtest scores). No scores were imputed for Advanced Placement or International Baccalaureate tests, since taking one of these tests does not indicate that a person has taken others.

4. ACT subtest scores were converted to SAT subtest scores where present, rather than imputing the missing SAT scores. The conversion table was taken from Dorans (1999).

Analytic Approach

In order to estimate the effect of location of college on likelihood of joining the Maryland workforce after college, we applied a propensity score matching approach (Austin 2011; Rosenbaum & Rubin, 1983).[5] Propensity score matching is used to impose a quasi-experimental design onto nonexperimental data sets (Holmes, 2013). In an experiment, random assignment of participants to conditions helps to control for the possibility of differences in extraneous variables, such as the participants' academic achievements, leading to group differences in the outcome of interest. In real extant data such relationships are likely to exist: a high school student with a higher GPA might be more likely to attend an out-of-state university because the student is more likely to receive merit-based financial aid to offset out-of-state tuition. We used propensity score matching to correct for preexisting differences between students who enrolled at a Maryland college and those who enrolled at an out-of-state college on covariates that could potentially affect the outcome. The propensity score model included all high school, demographic, and achievement covariates (see Table 2).[6] We selected one-to-one matching between students in the treatment condition (out-of-state college enrollment) and students in the control condition (Maryland college enrollment) and used a greedy matching algorithm with a caliper of 0.20 and no replacement. The matching procedure was repeated for each of the imputed data sets. Due to differences in the imputed values between the data sets, the number of students in the treatment condition that could successfully be matched to students in the control condition varied slightly, yielding slightly different sizes for the resulting matched data sets (14,518–14,556; see Table 3 below).

Figure 1 shows the distribution of propensity scores between the two groups prior to matching and Figure 2 shows the distribution after matching. A comparison of Figures 1 and 2 shows sufficient overlap of propensity scores for the students who attended college in Maryland and outside of Maryland, with overlap improving in the matched sample. Figure 3 shows the standardized mean differences (SMDs) for the variables included in the propensity score model in the unmatched and matched data sets. The SMD between the treatment and the control groups was below 0.1 for all covariates in all of the 20 matched data sets, indicating that differences between the groups were negligible (Austin, 2011; Normand et al., 2001). The SMD improved in the matched data sets when compared to the unmatched data set.

Logistic regression analyses were conducted with the matched data sets to explore whether enrolling at a college outside of Maryland affected the likelihood that a Maryland high school graduate would join the Maryland workforce after college after the groups were matched on all available covariates. Coefficients and variances from these analyses were statistically combined using Rubin's (1987) pooling methodology to generate a single set of results. Follow-up descriptive analyses examined the student characteristics of students who attended college out of state and returned to Maryland to join the workforce compared to out-of-state college students who did not return to Maryland to join the workforce.

5. We used the *Matching* package (Sekhon, 2011) in the *R* statistical environment (R Core Team, 2015).

6. The propensity model included the interaction between the SAT/ACT and PSAT indicator variables and the subtest scores rather than the main effect of the subtest scores (which would have resulted in the analysis excluding data from any students without SAT/ACT and PSAT scores).

Figure 1. Distribution of propensity scores in the in-state and out-of-state groups before matching

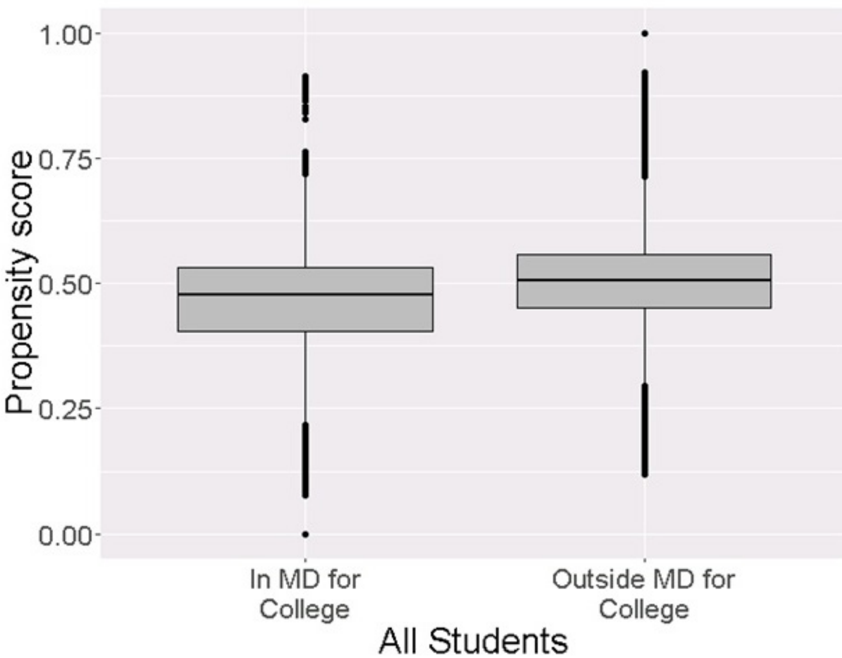


Figure 2. Distribution of propensity scores in the in-state and out-of-state groups after matching

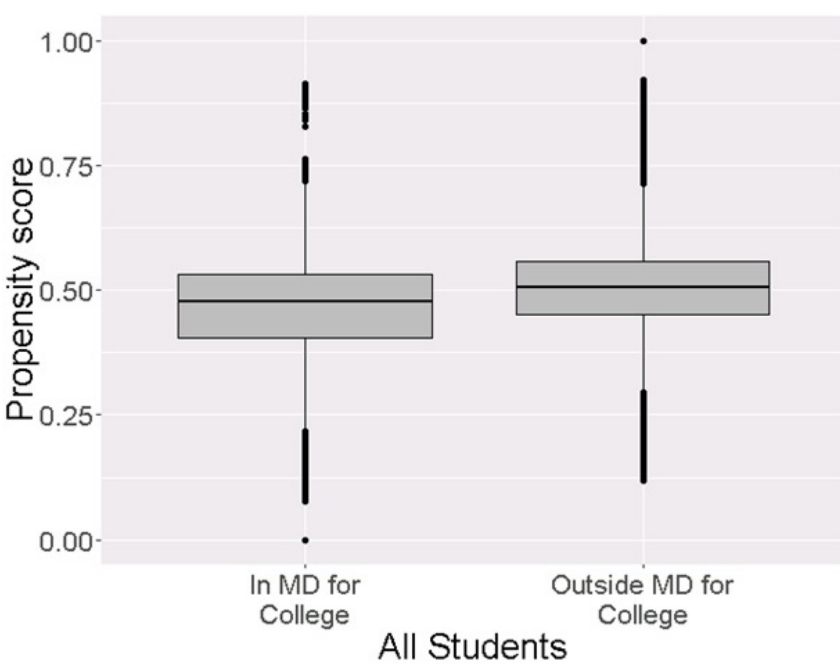
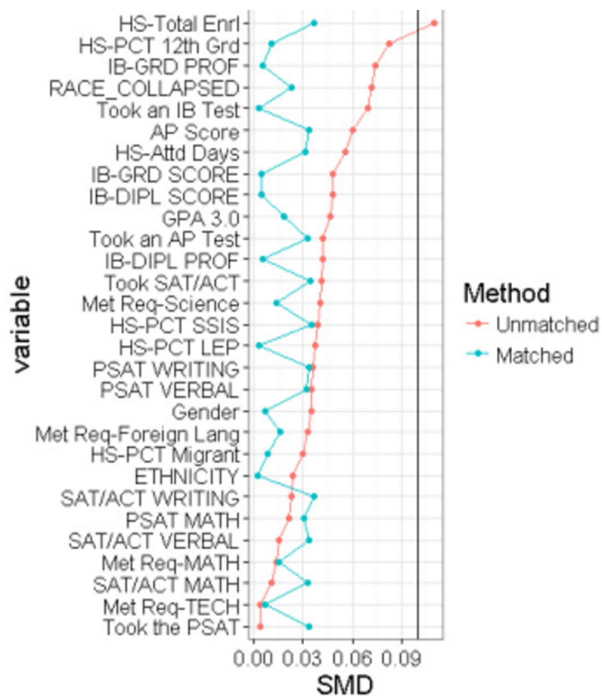


Figure 3. Standardized mean difference (SMD) on variables in the matched and unmatched samples



Note: HS-Total Enrl = Total enrollment in the student's high school

HS-PCT 12th Grd = Percent of the student's high school population in the 12th grade

IB-GRD PROF = Highest proficiency level on an International Baccalaureate test

RACE_COLLAPSED = Race category (Underrepresented minority vs. Not underrepresented minority)

Took an IB test = Did the student take at least one International Baccalaureate test?

AP score = Highest score on an Advanced Placement test

HS_Attd Days = Number of days the student attended high school in their final year

IB-GRD SCORE = Highest score on an International Baccalaureate test

IB-DIPL PROF = Highest proficiency on an International Baccalaureate diploma

Took SAT/ACT = Did the student take the ACT or SAT?

Met Req-Science = Did the student meet the requirements for rigorous high school program completion in science?

HS-PCT SSIS = Percent of student's high school in a special education program

HS-PCT LEP = Percent of the student's high school in an English proficiency program

PSAT WRITING = PreSAT writing score

PSAT VERBAL = PreSAT Verbal score

Gender = Gender

Met Req-Foreign Lang = Did the student meet the requirements for rigorous high school program completion in foreign language?

HS-PCT Migrant = Percent of the student's high school categorized as migrant

Ethnicity = Ethnicity

SAT/ACT Writing = SAT or converted ACT writing score

PSAT MATH = PreSAT math score

SAT/ACT Verbal = SAT or converted ACT verbal score

Met Req-Math = Did the student meet the requirements for rigorous high school program completion in math?

SAT/ACT Math = SAT or converted ACT math score

Met Req-TECH = Did the student meet the requirements for rigorous high school program completion in advanced technology education?

Took the PSAT = Did the student take the PSAT?

FINDINGS

Comparing Maryland College Students to Out-of-State College Students

Of the cohort of Maryland high school graduates included in the analyses, 48% initially enrolled in a college outside of Maryland. Table 2 presents the results comparing the demographic and achievement characteristics of Maryland public high school graduates who enrolled in college in state and out of state. Students enrolled outside of Maryland were less likely to have completed course requirements for both the University System of Maryland (USM) and a career and technology program, and were less likely to be Black or Asian and more likely to be White. In terms of academic variables, such as SAT score and whether the student had taken an Advanced Placement exam, the differences between the two groups are very slight.

Is There Brain Drain from Maryland?

The descriptive statistics in Table 2 indicate that the high school graduates in the sample who enroll in an out-of-state college differ from those who enroll in an in-state college. Using propensity score matching, we matched in-state and out-of-state enrollees on the variables shown in Table 2. It was then possible to examine whether there is a difference between the two matched groups in their likelihood of appearing in the Maryland employment records after college. Table 3 presents the results of the logistic regression analyses predicting workforce participation in Maryland with out-of-state 4-year college enrollment using the full sample and the matched sample. In the sample matched on all available demographic, academic achievement, and high school characteristics, enrollment at a college outside of Maryland had a negative relationship with an individual joining the Maryland workforce following college. We can transform the log-odds (indicated by the beta weight in Table 3) into odds to understand how likely a student in the matched data set who went to an out-of-state institution was to have participated in the Maryland workforce compared to one who went to a Maryland institution: e-1.13 = 0.323, or roughly one-third as likely. Across the matched data sets, 80% of students who enrolled at Maryland colleges had postcollege workforce records, compared to 57% of students who enrolled outside of Maryland. The coefficient size for the treatment was larger in the unmatched than the matched, indicating that propensity score matching eliminated some of the between-group differences that influenced the likelihood of joining the Maryland workforce. Even after propensity score matching, however, the relationship between location of initial college enrollment and likelihood of joining the Maryland workforce remains sizable.

Who Is Lost to Brain Drain from Maryland?

Table 4 displays the descriptive statistics for students who enrolled at a 4-year college outside of Maryland and who returned to Maryland for work, compared to students who enrolled at a 4-year college outside of Maryland and do not have Maryland employment records after college. Individuals who enrolled in college out of state and joined the Maryland workforce tended to have less-positive high school academic indicators than individuals who did not join the Maryland workforce

Table 3. Logistic regression with 4-year college enrollment outside of Maryland predicting workforce participation in Maryland

	Full Sample (N = 16,935)			Matched Sample ($N \geq$ 14,518)*		
Coefficients	Estimate	Std. Error	*p*	Estimate	Std. Error	*p*
(Intercept)	1.46	0.03	< 0.001	1.39	0.03	< 0.001
Outside of Maryland for College	–1.22	0.04	< 0.001	–1.13	0.04	< 0.001

* Sample size shown is the minimum of the range across the sets of matched data.

after enrolling in college out of state (e.g., lower SAT/ACT subtest scores). There was no difference between the two groups in the rate of enrolling in a graduate program.

DISCUSSION

This study examined the brain drain phenomenon in Maryland; specifically, we examined the characteristics of Maryland high school students who enrolled in college in state in comparison to those who enrolled in college out of state, whether those students who remained in state for college continue to remain in state for employment following graduation, and what differences exist between the two groups. The findings indicate that there is some degree of brain drain when Maryland public high school students enroll in colleges outside of Maryland. Students who enrolled in 4-year out-of-state colleges were less likely to join the Maryland workforce following college when compared to Maryland public high school students who enrolled in Maryland colleges (80% of students who enrolled at Maryland colleges had postcollege workforce records, compared to 57% of students who enrolled outside of Maryland). Furthermore, the individuals who return to the Maryland workforce after enrolling in out-of-state colleges tend to be lower-achieving students (with regard to high school achievement measures) than students who do not return to the Maryland workforce. This suggests that individuals with stronger academic indicators may be more likely to go on to employment outside of Maryland following enrollment in a college outside of Maryland than are individuals with less-positive academic indicators.

The findings from this study are generally consistent with prior research reporting brain drain from high school through college to the workforce (Groen, 2004; Perry, 2001). The majority of the Maryland public high school students in the sample initially enrolled at a Maryland institution, consistent with Hawley and Rork (2013) and Perry (2001). Also consistent with Perry (and with Groen, 2004), there was a negative relationship between enrollment in an out-of-state college and likelihood of returning to the original state of residence for employment. However, previous examinations of college graduate

Table 4. Demographic, achievement, college attendance, and degree characteristics of Maryland public high school graduates who enrolled in a 4-year out-of-state college by whether the person worked in Maryland after college

	Did not join the Maryland workforce (N ≥ 3,145)*	Did join the Maryland workforce (N ≥ 4,109)*
Count of college enrollment terms	M = 9.9; SD = 3.0	M = 9.5; SD = 3.7
Enrolled in a graduate program	20%	21%
Received a certificate	0 %	1%
Received an associate degree	1%	3%
Received a bachelor's degree	75%	69%
Received a master's degree	< 1%	3%
Female	54%	57%
Underrepresented minority	27%	35%
Hispanic or Latino	4%	3%
Highest AP test score	M = 3.7; SD = 1.4	M = 3.2; SD = 1.4
Highest IB diploma test score	M = 19.8; SD = 15.9	M = 17.2; SD = 14.0
Highest IB grade test score	M = 19.8; SD = 14.9	M = 17.2; SD = 14.0
Highest IB diploma proficiency	M = 2.4; SD = 1.9	M = 2.2; SD = 1.9
Highest IB grade proficiency	M = 5.4; SD = 1.1	M = 4.9; SD = 1.3
PSAT verbal	M = 53.6; SD = 11.2	M = 48.9; SD = 10.8
PSAT writing	M = 53.2; SD = 11.4	M = 48.5; SD = 11.0
PSAT math	M = 55.7; SD = 12.2	M = 50.3; SD = 11.4
Took the ACT/SAT	96%	92%
Took at least one IB exam	4%	3%
Took the PSAT	84%	80%
Took at least one AP exam	78%	63%
SAT/ACT math	M = 577.6; SD = 117.3	M = 526.2; SD = 112.3

SAT/ACT verbal	M = 566.1; SD = 112.1	M = 517.5; SD = 106.4
SAT/ACT writing	M = 561.8; SD = 112.6	M = 516.1; SD = 107.5
Met the rigorous high school program requirements for foreign language	77%	69%
Met the rigorous high school program requirements for math	68%	57%
Met the rigorous high school program requirements for science	44%	34%
Met the rigorous high school program requirements for advanced technology education	10%	8%
Completed high school with a cumulative GPA of 3.0 or higher	78%	64%

Note: * The samples sizes shown are the minimum of the range across sets of matched data. AP = Advanced Placement; IB= International Baccalaureate. These analyses include all individuals in the matched data sets who were in the treatment group (i.e., initially enrolled out of state); sample sizes shown are the minimum of the range across sets of matched data. Where available, ACT Reading and ACT English scores are summed, then converted into SAT verbal scores.

migration (Bui, 2016) reported that Maryland has a net gain with regard to the number of college graduates under 40: more graduates come into Maryland than leave. Unfortunately, it is not possible with the current data to see this positive difference, which would require access to the data of all college graduates across the United States, rather than just those who first graduated from a Maryland public high school or who attended Maryland postsecondary institutions. In other words, the results reported here indicate that brain drain occurs, but they do not speak to the sum total of postcollege individuals who join the Maryland workforce.

This study is limited in several ways. The available workforce data did not include self-employment, military service, federal employment, or independent contractors. A person who does not have workforce records following college enrollment could be unemployed, employed outside of Maryland, or employed in one of those excluded domains. To draw conclusions from differences in the number of in-state college enrollees and out-of-state enrollees who have workforce records, it is assumed that the likelihood of being employed in jobs in those excluded domains is the same for both groups. Furthermore, the propensity scores used to match the treatment and nontreatment groups in this study were calculated based on the variables available, and it is possible that there were unmeasured confounders, or other variables related to Maryland employment that were not included. For instance, information about students' specific socioeconomic status, their parents' education level, or the students' behavior during high school (e.g., if the student had suspensions or discipline referrals) might have improved the matching process and potentially influenced the results of the outcome analysis. Finally, this study retained only 29% of the 2009 Maryland high school graduates, and the students retained differed from those that were excluded on several indicators, including demographic characteristics and academic performance indicators. Therefore, the generalizability of this study is limited to students who matched the profile of included students.

POLICY IMPLICATIONS

Many states, such as Florida, Georgia, Missouri, and Texas, have adopted legislation designed to reward high-performing students with merit- or need-based assistance. These programs have differed in their impact on brain drain (Harrington et al., 2016; Hickman, 2009; Sjoquist & Winters, 2013; Zhang & Ness, 2010). The current study investigated the question of brain drain as it occurs at the intervention point of these kinds of programs: If a Maryland high school graduate is motivated to enroll at a Maryland college rather than an out-of-state college, is that person more likely to stay in Maryland to work? The results suggest that a program that increases the likelihood of a high school graduate attending an in-state college is likely to increase the number of high school graduates who stay in the state's workforce. Furthermore, other research suggests that out-of-state high school graduates who enroll at a state's colleges will not be as likely to stay in the state postcollege as are high school graduates who stay in state for college (Perry, 2001). This implies that retaining high school graduates in state for college is more likely to benefit a state's workforce than is attracting out-of-state students to its colleges. However, neither the current study nor Perry's investigation explored the types of employment held by different groups. It is possible that workers who originally live in other states tend to work at different jobs, or that students who go out of state for college and return to the original state's workforce work different jobs than those who stay in state for college and join the workforce. Furthermore, previous research suggests that programs designed to encourage in-state college enrollment may accomplish this goal but still fail to increase the number of individuals who join the state's workforce after college (Sjoquist & Winters, 2013). A solution could involve programs that encourage in-state enrollment for specific subgroups of high school graduates for whom in-state enrollment has the strongest relationship to likelihood of joining the original state's workforce.

FUTURE DIRECTIONS

To help states better understand the brain drain phenomenon and how to best mitigate its impact, future research should explore differences in rates of enrollment in public and private institutions for students who enroll at in-state versus out-of-state colleges. The approach taken to mitigate brain drain might depend on whether it is primarily students attending out-of-state private institutions who do not return to the state's workforce or primarily students attending out-of-state public institutions who do not return. A similar motivation exists for examining the location of the out-of-state institution (e.g., 250 miles or closer versus farther than 250 miles away, or colleges in specific states) and its effect on likelihood of returning to the original state's workforce after college. Future research on brain drain could also usefully investigate the types of employment held by former in-state versus out-of-state college students. It is possible that certain types of jobs tend to be held by people who went out of state for college.

CONCLUSION

This study used linked longitudinal data from the MLDS to investigate the full brain drain process from high school to college and to the workforce. The findings indicate that brain drain does exist in Maryland: Maryland public high school students who go out of state for college are less likely to be found in the Maryland workforce than are Maryland public high school students who stayed in state for college. The findings of this study contribute to the literature on brain drain in that they provide a direct examination of how enrollment in an out-of-state college affects the rate of joining the state's workforce while using propensity score matching to control for the differences that exist between these two groups at the outset. The demographic variables, academic indicators, and high school information available in the MLDS enabled the application of advanced statistical methods for this analysis in order to be more confident that similar groups of students, who differed only in the location of their initial college enrollment, were compared regarding their workforce outcome.

REFERENCES

Austin, P. C. (2011). An introduction to propensity score methods for reducing the effects of confounding in observational studies. *Multivariate Behavioral Research, 46*(3), 399–424.

Bui, Q. (2016). The states that college graduates are most likely to leave. *New York Times*, November 22, 2016. Retrieved September 12, 2017, from https://www.nytimes.com/2016/11/22/upshot/the-states-that-college-graduates-are-most-likely-to-leave.html.

Cooke, T. J., & Boyle, P. (2011). The migration of high school graduates to college. *Educational Evaluation and Policy Analysis, 33*(2), 202–213.

Dorans, N. J. (1999). Correspondences between ACT™ and SAT® I scores. College Board Report No. 99-1, ETS RR No. 99-2. College Entrance Examination Board, New York. Retrieved from https://www.ets.org/Media/Research/pdf/RR-99-02-Dorans.pdf.

Engelmyer, L. (2019). 2 key statistics for college cost comparison: Graduation rate and retention rate explained. *College Raptor*, February 21, 2019. Retrieved from https://www.collegeraptor.com/find-colleges/articles/college-comparisons/2-key-statistics-for-comparing-colleges-graduation-rate-and-retention-rate-explained/.

Finn, M., & Darmody, M. (2017). Examining student immobility: A study of Irish undergraduate students. *Journal of Higher Education Policy and Management, 39*(4), 423–434.

Groen, J. A. (2004). The effect of college location on migration of college-educated labor. *Journal of Econometrics*, 121(1–2), 125–142.

Harrington, J. R., Munoz, J., Curs, B. R., & Ehlert, M. (2016). Examining the impact of a highly targeted state administered merit aid program on brain drain: Evidence from a regression discontinuity analysis of Missouri's Bright Flight program. *Research in Higher Education, 57*(4), 423–447.

Hawley, Z. B., & Rork, J. C. (2013). The case of state funded higher education scholarship plans and interstate brain drain. *Regional Science and Urban Economics, 43*(2), 242–249.

Heller, D. E., & Rasmussen, C. J. (2002). Merit scholarships and college access: Evidence from Florida and Michigan. In D. E. Heller & P. Marin (Eds.), *Who should we help? The negative social consequences of merit scholarships* (pp. 25–40). Cambridge, MA: The Civil Rights Project at Harvard University.

Hickman, D. C. (2009). The effects of higher education policy on the location decision of individuals: Evidence from Florida's Bright Futures Scholarship Program. *Regional Science and Urban Economics, 39*(5), 553–562.

Holmes, W. M. (2013). *Using propensity scores in quasi-experimental designs*. Thousand Oaks, CA: Sage.

Ishitani, T. T. (2010). The determinants of out-migration among in-state college students in the United States. *Research in Higher Education, 52*(2), 107–122.

Kelchan, R., & Webber, D. A. (2018). Examining the interstate mobility of recent college graduates. *Educational Researcher, 47*(3), 213–215.

Kodrzycki, Y. K. (2001). Migration of recent college graduates: Evidence from the National Survey of Youth. *New England Economic Review*, 13–34.

National Institutes of Health (NIH). n.d. Research Training and Career Development, National Institutes of Health, U.S. Department of Health & Human Services, Washington, DC. Retrieved from https://researchtraining.nih.gov/resources/faq.

Normand, S. L. T., Landrum, M. B., Guadagnoli, E., Ayanian, J. Z., Ryan, T. J., Cleary, P. D., & McNeil, B. J. (2001). Validating recommendations for coronary angiography following an acute myocardial infarction in the elderly: A matched analysis using propensity scores. *Journal of Clinical Epidemiology, 54*(4), 387–398.

Perry, K. K. (2001). Where college students live after they graduate. ERIC Document Reproduction Service No. ED453739. National Center for Education Statistics, Washington, DC.

R Core Team (2015). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. Retrieved January 10, 2018, from http://www.R-project.org/.

Rosenbaum, P. R., & Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika, 70*(1), 41–55.

Rothwell, J. (2015). What colleges do for local economies: A direct measure based on consumption. Metropolitan Policy Program, Brookings Institution, Washington, DC.

Rubin, D. B. (1987). *Multiple imputation for nonresponse in surveys*. New York: Wiley.

Sekhon, J. S. (2011). Multivariate and propensity score matching software with automated balance optimization: The matching package for R. *Journal of Statistical Software, 42*(i07), 1–52. Retrieved January 10, 2018, from http://www.jstatsoft.org/v42/i07/.

Sinharay, S., Stern, H. S., & Russell, D. (2001). The use of multiple imputation for the analysis of missing data. *Psychological Methods, 6*(4), 317–329.

Sjoquist, D. L., & Winters, J. V. (2013). The effects of HOPE on post-college retention in the Georgia workforce. *Regional Science and Urban Economics, 43*(3), 479–490.

U.S. Department of Education (2015). Residence and migration of all first-time degree/certificate-seeking undergraduates in 4-year degree-granting postsecondary institutions who graduated from high school in the previous 12 months, by state or jurisdiction: Fall 2014 [Table]. Institute of Education Sciences, National Center for Education Statistics, U.S. Department of Education, Washington, DC. Retrieved January 10, 2018, from https://nces.ed.gov/programs/digest/d16/tables/dt16_309.30.asp?current=yes.

Winters, J. V. (2015). The production and stock of college graduates for U.S. states. Working Paper 15-246, W.E. Upjohn Institute for Employment Research, Kalamazoo, MI.

Zhang, L., & Ness, E. C. (2010). Does state merit-based aid stem brain drain? *Educational Evaluation and Policy Analysis*, 32(2), 143–165.

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