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

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If you have questions regarding this publication, please contact mlds.center@maryland.gov.

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Executive Summary

Once Maryland students graduate from high school, they have the opportunity to remain in-state for postsecondary education or leave Maryland for further education or employment. This loss of graduates to other states has been termed “brain drain” and is a concern for state policymakers (Zheng & Ness, 2010). Several states have adopted merit-based programs designed to retain college-educated individuals in order to support the state workforce, but outcomes have been inconsistent across the high school-to-college and college-to-workforce transition points. This study uses data from the Maryland Longitudinal Data System (MLDS) to link student high school records to college and employment information in order to determine the extent of brain drain in Maryland. Findings indicated that brain drain does exist in Maryland to some degree, as students who attended out-of-state colleges were less likely to return to the Maryland workforce when compared to students who attended in-state colleges (80% of students who enrolled at Maryland colleges had post-college workforce records, compared to 57% of students who enrolled outside Maryland). Additionally, the students lost to brain drain tended to be higher achieving students. Policy implications and directions for future research on brain drain in Maryland are discussed.

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Introduction

States invest significant funds in public school systems in an effort to support and prepare students for success. One of the direct returns on the investment in public education would take the form of in-state workforce participation (Winters, 2015). The loss of in-state high school and college graduates to other states has been termed "brain drain" by researchers and is a concern for state policymakers (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 full picture of the brain drain phenomenon, it is important to consider student migration (that is, movement of students out of their original state of residence) at both transition points. To do so, it is necessary to follow students from high school, through college, and into the workforce.

This report describes previous research on the topic of brain drain, with regard to high school graduates going out of state for college as well as in-state college graduates going to the out-of-state workforce. Data from the Maryland Longitudinal Data System (MLDS) was used to examine the movement of Maryland public high school graduates to college and then to the Maryland workforce. Maryland high school graduates who enrolled at out-of-state colleges were compared to those who enrolled at Maryland colleges, and the individuals who return to the Maryland workforce after being enrolled at out-of-state colleges were compared to those who do not return to Maryland for employment.

Background

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 out-of-state for 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 small, densely populated states, such as Maryland, or larger populous states like Illinois (Cooke & Boyle, 2011). Less densely populated states, 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 incredible variation in states in terms of geographic size, population, and number and quality of higher education institutions means that considering migration of students state-by-state provides a more accurate picture of the brain drain phenomenon than a nationwide estimate alone.

The National Center for Education Statistics (NCES) reports migration for students entering postsecondary institutions. The most recent migration data available as of this report indicates that eleven states, including Maryland, reported a net loss of first-time degree/certificate seeking students at four year degree-granting public institutions in 2014 (U.S. Department of Education, 2015). Maryland reported a net loss of 8,881 of these students, the fifth largest net loss.

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 (NLSY, a product of the U.S. Bureau of Labor Statistics) relocate to a different state within five 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). Relocation decisions are influenced by personal characteristics as well as state economies, population and amenities, and a history of moving across state lines as a child (Kodrzycki, 2001). Ishitani (2010) investigated the characteristics of students who attended college in-state then decided to leave the state following graduation using data from the National Educational Longitudinal Study (NELS: 88/2000) and Postsecondary Education Transcript Study (PETS: 2000). The 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. Students who were more likely to stay in the same state after college attendance were more often Hispanic or attended college in states with a higher gross domestic product (Ishitani, 2010).

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 2000-2015 (Bui, 2016). This means that there was an approximately 1% positive difference in the number of college graduates under 40 who moved to Maryland compared to the number who left.

Brain Drain from High School to College and the Workforce

Previous research has 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; Perry, 2001). Groen (2004) investigated brain drain using two separate longitudinal datasets, both including students who initially enrolled in a 4-year college in the 1970s (the Mellon Foundation's College and Beyond dataset [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-state lived 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) investigated brain drain using data from the NCES Baccalaureate and Beyond Longitudinal Study. She 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 college in-state were more likely to live in the state of the college from which they had graduated than were students who attended college out-of-state (Perry, 2001).

State-Sponsored Programs to Alleviate the Brain Drain

Groen (2004) concluded that the small relationship he found between college location and location of later employment provided only weak justification for the type of merit-based scholarships designed to keep high-ability students in-state for college. Some studies have more directly examined the effects of state-sponsored programs designed to increase the number of college-educated individuals in the state workforce by keeping more in-state high school graduates in the state for college. Hickman (2009) investigated whether a merit aid program in Florida increased the retention of native-born Floridians after college. His analysis found that there was over a 3% increase in the likelihood that a native Floridian who had at least some college would be residing in Florida after college following the program's introduction. However, Hickman did not investigate whether the residents who attended college did so in Florida or outside of Florida, so he did not report any changes in the rate at which Florida high school graduates remained in-state for college or the rate at which these in-state college students remained in Florida after college. Hawley and Rork (2013) investigated the impact of state-sponsored scholarship programs on both enrollment of in-state students and on migration of college graduates out of the state for 21 states that had implemented a state-sponsored scholarship program. They used individual level data from the Census Public Use Micro-Sample (PUMS) as well as aggregated data from the NCES Integrated Postsecondary Education Data System (IPEDS). The IPEDS data indicated that the majority of new freshman enrollments were at in-state institutions, consistent with Perry (2001). Hawley and Rork found a delayed positive effect of program introduction on enrollment of in-state students, indicating that these programs address the first transition associated with brain drain: enrollment in in-state rather than out-of-state colleges. They also found a decrease in out-of-state migration for workers in certain age brackets following the introduction of the scholarship programs, but an increase in out-migration for workers in other age brackets, leading to an overall non-significant effect of scholarship programs on out-migration. However, the PUMS data they used to investigate migration at the individual level did not include whether the person had attended college in his or her original state of residence, and so could not speak to brain drain across both transition points. Sjoquist and Winters (2013) were able to explore the impact of a scholarship program on both in-state enrollment at Georgia colleges and on post-graduation retention of students using the PUMS data. They found that enrollment of Georgia high school graduates at public universities in Georgia increased in the years following the implementation of the program, as did graduation rates from these institutions. However, they also found that the percentage of students who attended college in-state and were in the Georgia workforce several years after college was actually slightly lower after the program's introduction. They suggested that the scholarship program may have kept more students in-state for college but that many of these students still left the state after college. The results of Hickman (2009), Hawley and Rork (2013), and Sjoquist and Winters (2013) indicate that programs designed to address brain drain have had mixed results.

The Current Study

This study aims to bridge a gap in the literature on brain drain by examining the enrollment of Maryland public high school graduates at in-state and out-of-state colleges (both public and private) and the post-college participation of these individuals in the Maryland workforce. The current literature generally focuses on either the high school to college transition, or the college to workforce transition, possibly due to the difficulty of obtaining linked longitudinal data over time. Hawley and Rork (2013), Hickman (2009), and Sjoquist and Winters (2013) investigated brain drain at both transition points, but did so with separate samples because their individual-level data did not include the location of the college attended (i.e., in-state versus out-of-state). While some research has been able to longitudinally investigate the full path of brain drain, these studies are limited in only considering college graduates (Perry, 2001), or examining employment location after a considerable time gap (Groen, 2004). These studies also controlled for a limited number of pre-existing differences between students who enrolled in-state and those who enrolled out-of-state (e.g. SAT scores, marital status).

This report addresses some of the limitations of prior research using data from the Maryland Longitudinal Data System (MLDS). MLDS data link high school, college, and workforce records across multiple years for Maryland public high school attendees. These data were used to examine whether Maryland public high school graduates who enrolled in a four-year college out-of-state were less likely to be employed in Maryland following college compared to Maryland public high school graduates who enrolled at in-state four-year colleges. Demographic variables, academic indicators, and high school characteristics were controlled for when considering the likelihood that a student enrolled out-of-state, and the relationship between these variables and in-state versus out-of-state college enrollment was controlled for during the investigation of the relationship between enrollment location and Maryland employment after college. This approach allowed for the isolation of the relationship between location of college enrollment and post-college participation in the Maryland workforce.

Research Questions

The analyses described in this report used linked longitudinal data from the MLDS to answer three 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 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 (i.e., who is lost to brain drain in Maryland)?

This research addresses topics directly related to two of the MLDS Center Research Agenda questions:

1. What percentage of Maryland high school exiters go on to enroll in Maryland postsecondary education?
2. Are exiters of Maryland colleges successful in the workforce?

Method

Sample Selection

The data used for this report are from the Maryland Longitudinal Data System (MLDS), which contains linked longitudinal data from three State agencies.[1] The Maryland State Department of Education (MSDE) provides data for public Pre K-12 students and schools. The Maryland Higher Education Commission (MHEC) provides data for Maryland public and private college students and colleges. The Department of Labor Licensing and Regulation (DLLR) provides data for Maryland employees 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. Out-of-state college enrollment and degree information is obtained through the National Student Clearinghouse (NSC).[2]

A flowchart displaying the sample selection process is shown in Figure 1. All Maryland public high school students who graduated in academic year 2008-2009[3] were identified. We selected this cohort of graduates to allow sufficient time for the student to complete postsecondary education at a 4-year college and to find employment.[4] We next identified those high school graduates who had at least one record of enrollment in an undergraduate program between the 2010 and 2016 academic years.[5] Of the approximately 58,000 Maryland high school graduates in 2009, 79% had at least one term of college undergraduate enrollment from 2010-2016. We further focused on 2009 high school graduates whose first year of college enrollment occurred in 2010, excluding those who enrolled in college in 2011 or later, to allow adequate time for the completion of undergraduate education. Of the students who enrolled in an undergraduate program, 76% had a record of college enrollment in 2010.

The vast majority (~97%) of students who initially enrolled in 2-year institutions enrolled at Maryland institutions. In order to make the group of in-state college enrollees included in this analyses as comparable as possible to the group of out-of-state college enrollees, we chose to focus on 2009 high school graduates whose initial enrollment was in a 4-year institution (public or private). Of the remaining students initially enrolled in 2010, 54% enrolled at a 4-year

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

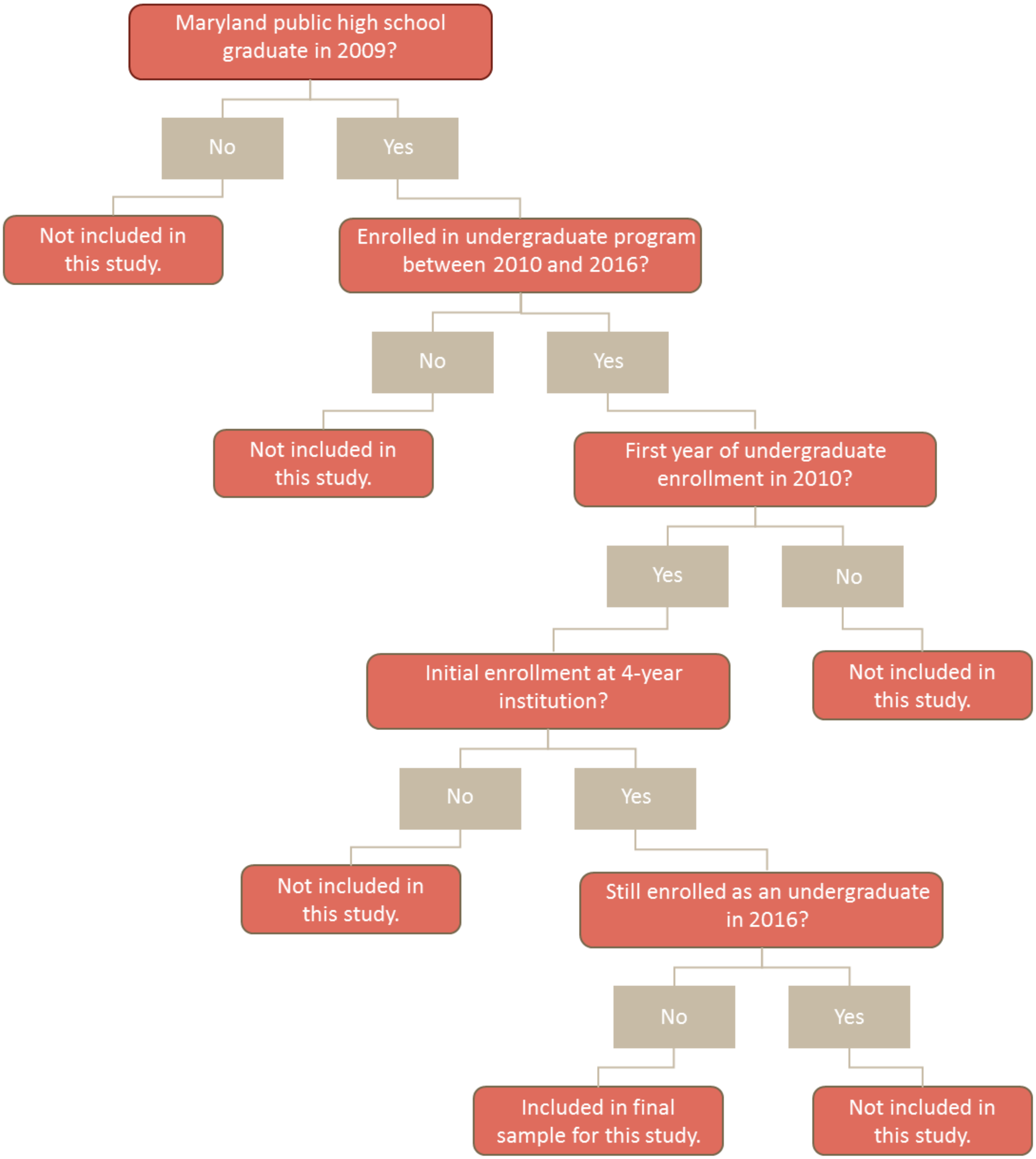
[2] For more information, visit http://www.studentclearinghouse.org/

[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 Fall 2008.

[4] The Maryland workforce data are received for each quarter in the calendar year. At the time this report was written, Maryland workforce data were available through the 4th quarter of 2016.

[5] A small number of students who graduated from a Maryland high school in 2009 (*N* = 64, ~0.1%) did not have a record of undergraduate enrollment, but did have a record of graduate enrollment. Because particulars of undergraduate enrollment could not be determined for these individuals, they were coded as not having enrolled in college.

Figure 1. Sample Selection



Note: Years represent academic years, where the year in text represents the year of the spring semester. For example, 2009 refers to the 2008-2009 academic year.

college. Finally, we investigated the latest year of undergraduate enrollment for each individual. Although all these students initially enrolled at a 4-year college in 2010, and thus had 6 years to complete their undergraduate education as of academic year 2015, students may have experienced breaks in enrollment or other events slowing completion. To focus on the role of in-state versus out-of-state college undergraduate enrollment on likelihood of joining the Maryland workforce after undergraduate education, we excluded the data of 11% of the remaining individuals in the sample 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. Differences in demographic and achievement variables between the students included in these analyses and those whose data were excluded in one of the steps above can be seen in Appendix A.

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, academic achievement indicators, 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 [FARMS]). Due to the small number of students in some race categories, race categories were collapsed into under-represented minorities (URM; Black, Native Hawaiian or Other Pacific Islander, American Indian or Alaskan Native, Two or More Races) and not under-represented minorities (White, Asian). These categories are consistent with the National Institutes of Health (NIH) definition of URM in Sciences (https://researchtraining.nih.gov/resources/faq). Workforce participation in Maryland was coded if the student had at least one workforce record that occurred in the 4th fiscal quarter of the same calendar year as their last year of college enrollment, or any quarter of a later year. This 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. The MLDS workforce data do not include records for individuals working for the federal government or for employers outside of Maryland. Also, instances of self-employment or military employment are not included in these data. The latest workforce data available at the time of these analyses were for FY 2016.

Analyses

The principle data analyses were conducted over three steps. First, missing data were handled using multiple imputation (Sinharay, Stern, & Russell, 2001; see Appendix B for details). Second, a propensity score matching approach (Austin 2011; Rosenbaum & Rubin, 1983) was used to control for differences between students who enrolled in an out-of-state college and those who enrolled in Maryland for college (see Appendix C for details). Last, a logistic regression analysis was conducted with the matched sample to explore whether enrolling at a college outside of Maryland affected the likelihood of a Maryland high school graduate joining the Maryland workforce after college. In supplemental analyses, we also explored whether out-of-state enrollees who returned to the Maryland workforce after college differed from those who did not return to the Maryland workforce after college.

Findings

Comparing Students who Enrolled in Maryland 4-Year Colleges and Students who Enrolled in Out-of-State 4-Year Colleges

Of the cohort of Maryland high school graduates included in analyses, 48% initially enrolled in a college outside of Maryland. Table 1 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.[6] 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, students who enrolled at colleges outside of Maryland had slightly higher average scores on the SAT/ACT and were slightly less likely to have graduated from high school with a GPA of 3.0 or higher.

Does Brain Drain Exist in Maryland?

The descriptive statistics in Table 1 indicate that the high school graduates in the sample who enroll out-of-state for college differ from those who enroll in Maryland for college (see Appendix D for a table comparing high school variables between the two enrollment groups). Using regression, the individual relationships between each of these variables were combined into a single propensity score representing likelihood of enrolling at an out-of-state college, which was used to match in-state and out-of-state enrollees. 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 2 presents the results of the logistic regression analyses using out-of-state 4-year college enrollment to predict workforce participation in Maryland 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 joining the Maryland workforce following college. The coefficient for college location indicates that students who enrolled in college outside of Maryland were about one-third less likely to appear in the Maryland workforce after college. Across the matched datasets, 80% of students who enrolled at Maryland colleges had post-college workforce records, compared to 57% of students who enrolled outside Maryland. These percentages can be compared to those for all students in the sample (i.e., before propensity score matching): 81% for students who enrolled at a Maryland college compared to 56% for those who enrolled outside Maryland. The

[6] We did not conduct statistical tests of the differences between groups in Table 1; we are concerned with the practical difference between the groups, rather than statistically significant differences.

Table 1. Demographic and Achievement Characteristics for Maryland Public High School Graduates who Enrolled in 4-Year Colleges Outside and Inside of Maryland

	Outside Maryland (*N* = 8,145)	Inside Maryland (*N* = 8,790)
HS Program Completion - Met requirements for:		
Approved Career and Technology program	2%	2%
Approved USM and occupational program	8%	11%
Approved USM	78%	77%
Non Completer	< 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 or 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 HS Program Requirements for:		
Foreign Language	71%	73%
Math	61%	62%
Science	38%	39%
Advanced Technology Education	8%	8%
Completed HS with a cumulative GPA ≥3.0	69%	71%

Notes: USM= University System of Maryland, AP= Advanced Placement, IB= International Baccalaureate, HS = high school, GPA= Grade Point Average. Where available, ACT Reading and ACT English scores are summed, then converted into SAT Verbal scores.

Table 2. Logistic Regression with Enrolled at a 4-Year College Out-of-State Predicting Workforce Participation in Maryland						
	Full sample (*N* = 16,935)			**Matched Sample (*N* >= 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 Maryland for College	-1.22	0.04	<0.001	-1.13	0.04	<0.001
* The full sample included 2009 Maryland public high school graduates who enrolled at a 4-year college in 2010 and were not enrolled in an undergraduate program in 2016. The matched sample is a subset of these individuals where individuals who initially enrolled at an out-of-state college were matched to those who initially enrolled at a Maryland college based on propensity scores. * Sample size shown in the minimum of the range across the sets of matched data						

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, the relationship between location of initial college enrollment and likelihood of joining the Maryland workforce remains sizable.

Who is Lost to Brain Drain in Maryland?

Table 3 displays the descriptive statistics for people who enrolled at a 4-year colleges outside of Maryland and returned to Maryland for work compared to students who enrolled at a 4-year colleges 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 after enrolling in college out-of-state. There was no difference between the two groups in the rate of enrolling in a graduate program. 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. However, the Maryland employment data do not include military service, federal government employment, self-employment, or unemployment, and thus, we cannot definitively say that individuals who were not found in the Maryland workforce were employed out-of-state. A supporting comparison, contrasting individuals with post-college employment in Maryland by whether they enrolled at a 4-year college out-of-state or in Maryland, is presented in Appendix E.[7]

[7] We did not conduct statistical tests of the differences between groups in Table 2. We focus on the practical difference between the groups, rather than statistically significant differences.

Table 3. 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%
Under-represented 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 HS Program Requirements for Foreign Language	77%	69%
Met the Rigorous HS Program Requirements for Math	68%	57%
Met the Rigorous HS Program Requirements for Science	44%	34%
Met the Rigorous HS Program Requirements for Advanced Technology Education	10%	8%
Completed high school with a cumulative GPA of 3.0 or higher	78%	64%

Notes: These analyses include all individuals in the matched datasets 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. AP = Advanced Placement, IB = International Baccalaureate, HS = high school, GPA= Grade Point Average.
Where available, ACT Reading and ACT English scores are summed, then converted into SAT Verbal scores.
* The samples sizes shown are the minimum of the range across sets of matched data.

Discussion

This study expands on the current literature by exploring the impact of in-state versus out-of-state college enrollment on likelihood of working in the state of origin while controlling for many variables that may also be related to employment outcomes (e.g., high school achievement indicators). 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 post-college workforce records, compared to 57% of students who enrolled outside Maryland). Further, 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.

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 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 post-secondary institutions. In other words, the results reported here indicate that brain drain occurs, but do not speak to the sum total of post-college 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 these 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 these types of jobs is the same for both groups. Further, propensity scores used to match the treatment and non-treatment groups in this study were based on the variables available, and may not have captured other important variables related to Maryland employment. For instance, information about students' socio-economic status (SES), their parent's education level, or the students' behavior during high school, such as suspensions or referrals, may have improved the matching process and potentially influenced the results of the outcome analysis.

Policy Implications

Many states, such as Texas, Georgia, and Florida, 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 (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 Maryland high school graduate attending a Maryland college is likely to increase the number of Maryland high school graduates who stay in the Maryland workforce. Further, other research suggests that out-of-state high school graduates who come to Maryland colleges will not be as likely to stay in Maryland post-college as Maryland high school graduates who stay in-state for college (Perry, 2001). This suggests that retaining high school graduates in-state for college is more likely to benefit the Maryland workforce than is attracting out-of-state students to Maryland 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 lived in other states tend to work at different jobs, or that students who go out-of-state for college and return to the Maryland workforce work different jobs than those who stay in Maryland for college and join the workforce. Further, 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 may 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 Maryland workforce.

Future Research

The Maryland Longitudinal Data System offers many opportunities for additional research relevant to brain drain in Maryland. Understanding of this topic would benefit from future research examining the retention of college students, including out-of-state college students, in the Maryland workforce. The current study started with Maryland public high school graduates, rather than all students beginning in college, in order to investigate the full brain drain process from high school to college to the workforce. It is possible that Maryland retains a sizeable percentage of the students that enroll in Maryland colleges, regardless of their state of origin. It would also be useful for future research to explore differences in rates of enrollment in public and private institutions for students who enroll in Maryland versus out-of-state colleges. The approach taken to mitigate brain drain may depend on whether it is primarily out-of-state private institution students who do not return to the Maryland workforce or primarily out-of-state public institution students. A similar motivation exists for examining the location of the out-of-state institution (e.g., within 250 miles versus further than 250 miles away, or colleges in specific states) and its effect on likelihood of returning to the Maryland workforce after college. The MLDS contains information about the institutional enrollment for each public high school graduate, so it would be possible to investigate these questions using MLDS data.

Future research on brain drain could also usefully investigate the types of Maryland 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. The workforce data in the MLDS include North American Industry Classification (NAIC) codes associated with each record, so it would be possible to explore questions related to types of employment, at least at a sector/industry level, using the MLDS data. Finally, it would be informative to explore the relationship between scholarship and grant programs and brain drain in Maryland, similar to the way this question has been explored in other states (e.g., Sjoquist & Winters, 2013). The MLDS data include information on grants and scholarships at the individual level, so it would be possible to directly investigate how likelihood of staying in Maryland after college differs for students who receive a grant or scholarship when compared to students who do not.

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 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.

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Appendix A: Variable Summaries by Inclusion in Analyses

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

	Data not included (*N* = 41,461)	Data included (*N* = 16,935)
HS Program Completion -Met requirements for		
Approved Career and Technology program	13%	2%
Approved USM and occupational program	10%	9%
Approved USM	46%	78%
Non Completer	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 or 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 HS Program Requirements for:		
Foreign Language	33%	72%
Math	24%	61%
Science	12%	39%
Advanced Technology Education	7%	8%
Completed HS with a cumulative GPA ≥3.0	26%	70%

Notes: Students whose data were included in analyses graduated from a Maryland public HS in 2009, enrolled at a 4-year college in 2010, and were not enrolled in any undergraduate program in 2016.

USM= University System of Maryland, AP= Advanced Placement, IB= International Baccalaureate, HS=high school, GPA= Grade Point Average

Where available, ACT Reading and ACT English scores are summed, then converted into SAT Verbal scores.

High School variable values for students whose data were included in the analyses and those whose data were not included

	Data not included (*N* = 41,461)	Data included (*N* = 16,935)
Local School System of High School:		
a	1%	1%
b	9%	7%
c	13%	12%
d	2%	3%
e	1%	0%
f	4%	4%
g	2%	1%
h	4%	3%
i	1%	0%
j	5%	6%
k	1%	0%
l	5%	4%
m	5%	10%
n	0%	0%
o	15%	24%
p	15%	13%
q	1%	1%
r	2%	1%
s	0%	0%
t	1%	0%
u	3%	1%
v	2%	1%
w	1%	1%
x	8%	6%
School Type:		
High	92%	96%
Combine	2%	1%
Vocational/Technical	4%	3%
Special Education	0%	0%
Alternative	2%	0%
Charter	0%	0%
HS Adequate Yearly Progress Status Code:		
0	13%	8%
1	86%	92%
'Missing'	1%	0%
Free and Reduced Meals Student Count:	*M* = 372.18; *SD* = 267.06	*M* = 320.03; *SD* = 254.59
Special Education Student Count:	*M* = 139.32; *SD* = 63.48	*M* = 138.37; *SD* = 63.45

Migrant Student Count:	*M* = 0.05; *SD* = 0.4	*M* = 0.03; *SD* = 0.3
ESL/LEP Student Count:	*M* = 40.16; *SD* = 77.92	*M* = 41.54; *SD* = 70.39
Total Enrollment:	*M* = 1479.95; *SD* = 566.71	*M* = 1622.64; *SD* = 529.81
Grade 12 Enrollment:	*M* = 337.37; *SD* = 126.98	*M* = 378.64; *SD* = 124.48
School Open Days	*M* = 179.51; *SD* = 3.66	*M* = 179.87; *SD* = 0.64
School Open Days Through March 15:	*M* = 123.54; *SD* = 6.66	*M* = 122.62; *SD* = 5.34
Percent Free and Reduced Meal Students:	27%	21%
Percent Special Education Students:	10%	9%
Percent Migrant Students:	0%	0%
Percent ESL/LEP Students:	2%	2%
Percent Grade 12 of Total Enrollment:	23%	23%
NCES Program Type:		
Regular School	94%	97%
Special Education School	0%	0%
Vocational Education School	4%	3%
Alternative Education School	2%	0%
'Missing'	0%	0%
Magnet School Status:		
School-wide Magnet	1%	2%
Targeted Magnet	14%	13%
Non-magnet	85%	85%

Notes: Students whose data were included in analyses graduated from a Maryland public HS in 2009, enrolled at a 4-year college in 2010, and were not enrolled in any undergraduate program in 2016.

Appendix B: Multiple Imputation

Multiple imputation (Sinharay, Stern, & Russell, 2001), which uses an individual's existing variable values and observed patterns across the dataset to extrapolate the likely values for variables the individual is missing, was used to handle missing data in this analysis. A set of likely values was generated for each missing data point, which captures some degree of the uncertainty associated with the missingness in the data by postulating a range of possible values rather than a single value. The result of the imputation process is a set of datasets, each including a different pattern of imputed values for the missing values in the original dataset. Analyses are then conducted with each of the datasets, and results are combined to produce the final set of results. In line with current best practices for multiple imputation (Graham, Olchowski, & Gilreath, 2007), we imputed 20 datasets. Propensity score matching was then conducted separately for each imputed dataset. Similarly, the logistic regression predicting likelihood of being in the Maryland workforce after college from the location of initial college enrollment (Maryland vs. out-of-state) was fit to each dataset, now containing only the matched pairs of treatment and non-treatment individuals, separately. To generate overall results, the estimates and variances of those estimates were combined in a method consistent with previous studies (e.g., Marshall, Altman, Holder, & Royston, 2009; Rubin, 1987). The end product is a single set of regression results.

While multiple imputation can address missing data readily, it is important in the current dataset to consider the source of the missingness, and whether the missingness is indicative in and of itself. In conducting data imputation, we assumed that high school information, such as the proportion of students eligible for free and reduced price meals (FARMS) at a given high school, was missing at random conditional on known variables, and 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 translated ACT subtest scores into SAT scores.[8] Scores were imputed if the person had an existing score on one or more of the subtests; if the person did not have a score on any SAT or ACT subtest, no scores were imputed (~6% of the sample). A similar process was followed for scores on the PSAT subtests (~18% of students were missing all PSAT subtest scores). No scores were imputed for Advanced Placement or International Baccalaureate tests.

[8] Conversion table provided in https://www.ets.org/Media/Research/pdf/RR-99-02-Dorans.pdf

Appendix C: Propensity Score Matching

Propensity score matching (Austin 2011; Rosenbaum & Rubin, 1983) was used to control for differences between Maryland public high school graduates who enrolled at out-of-state colleges (the treatment) and those who enrolled at in-state colleges to assess the relationship between location of initial enrollment and post-college participation in the Maryland workforce (the outcome). The gold standard approach for estimating the impact of a treatment on an outcome is a randomized control trial in which each member of the sample has an equal probability of being assigned to the treatment group versus the non-treatment group (Austin, 2011). Randomized assignment to the treatment group greatly reduces the likelihood of confounding the treatment with covariates that may also affect the outcome. In contrast, observational studies often involve strong relationships between covariates and assignment to the treatment group, making it difficult to determine whether it is the treatment that has influenced the outcome or the treatment's relationship with some covariate. In these cases, there are statistical techniques that can be applied to mimic a randomized control trial design using observational data. Propensity score matching involves modeling the conditional probability of assignment to the treatment given a person's values on a set of covariates (Austin, 2011; Guo & Fraser, 2014; Rosenbaum & Rubin, 1983; Rubin, 1997). This model generates a propensity score for each person in the dataset that represents their likelihood of belonging to the treatment group; in effect, the model collapses the relationship between all covariates and the treatment condition into a single value for each person (Rubin, 1997). Individuals from the treatment group are then matched to individuals from the non-treatment group based on the propensity score, such that membership in the treatment group becomes the principal difference between the two groups.

For each of the 20 datasets resulting from the missing data imputation, we modeled the relationship between high school achievement indicators, demographic variables, and school characteristics (e.g., the percent of students eligible for free and reduced price meals [FARMS]) and the treatment, having an initial college enrollment outside of Maryland. In the case of IB, AP, SAT/ACT, PSAT scores, the interaction between the score and the indicator of having taken that measure was included in the model but the main effects were not. This approach allowed us to model the relationship between scores and likelihood of going outside of Maryland for college for only those students who have scores without necessitating the case-wise exclusion of individuals who do not have scores. Once the model was fit, it was possible to generate a propensity score for each person in the dataset, representing their likelihood of belonging to the treatment group (Rubin, 1997). Individuals in the non-treatment group were then matched to those in the treatment group based on the propensity score, resulting in a dataset where the people in the treatment group match those in the non-treatment group as much as possible based on available information.

We generated sets of matched pairs for each imputed dataset using the *Matching* package (Sekhon, 2011) in the *R* statistical environment (R Core Team, 2015). We selected 1-to-1 matching and used a greedy matching algorithm with a caliper of 0.20 and no replacement. Figure C.1 shows the distribution of propensity scores before and after matching for one of the imputed datasets. Students who went out of state for college had a higher mean propensity score when looking across the entire sample, but the set of matched pairs had similar propensity scores across the two groups (see Figure C.1).

Propensity score matching resulted in a dataset with equal numbers of students who enrolled in an out-of-state college and who enrolled in a Maryland college. In each of the 20 imputed datasets, approximately 86% of the cases were retained for the outcome analysis after propensity score matching. Because the non-treatment group outnumbered the treatment group, some in-state students did not have an out-of-state match and their data were excluded from analyses. In addition, a few students in the treatment group could not be matched within the parameters we set for match quality, and these data were also excluded. The number of individuals included in each of the 20 datasets in the outcome analyses was approximately 14,500 (*Range* = 14,518 - 14,556, depending on the imputed dataset). Note that the differing *N* for each matched dataset is due to different imputed values leading to different propensity scores, changing the number of individuals in the treatment group who could be successfully matched to an individual in the non-treatment group. The results of our matching procedure retained ~89% of the students in the treatment group in each of the 20 datasets.

Figure C.1. Distribution of Propensity Scores Before and After Matching

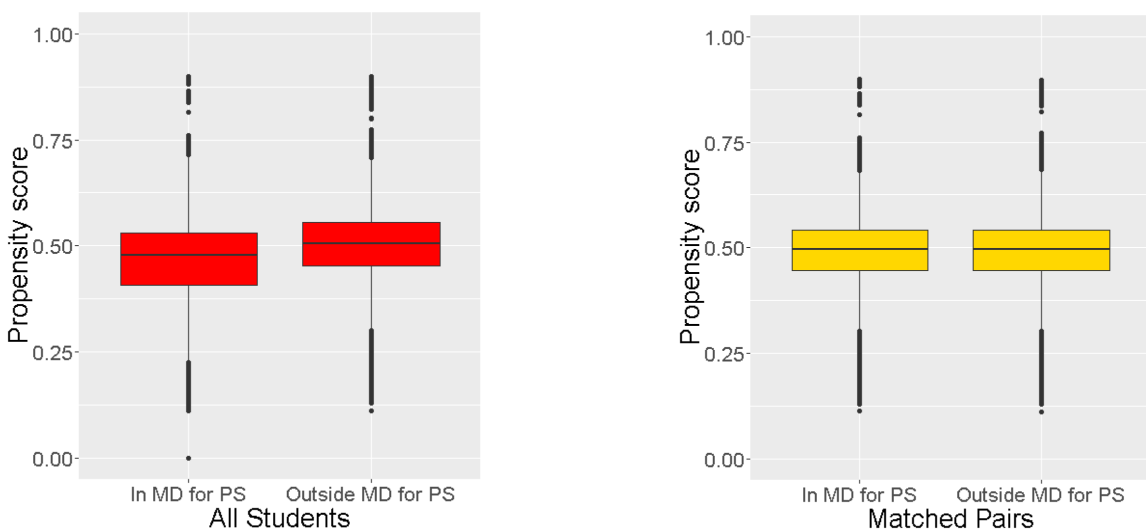
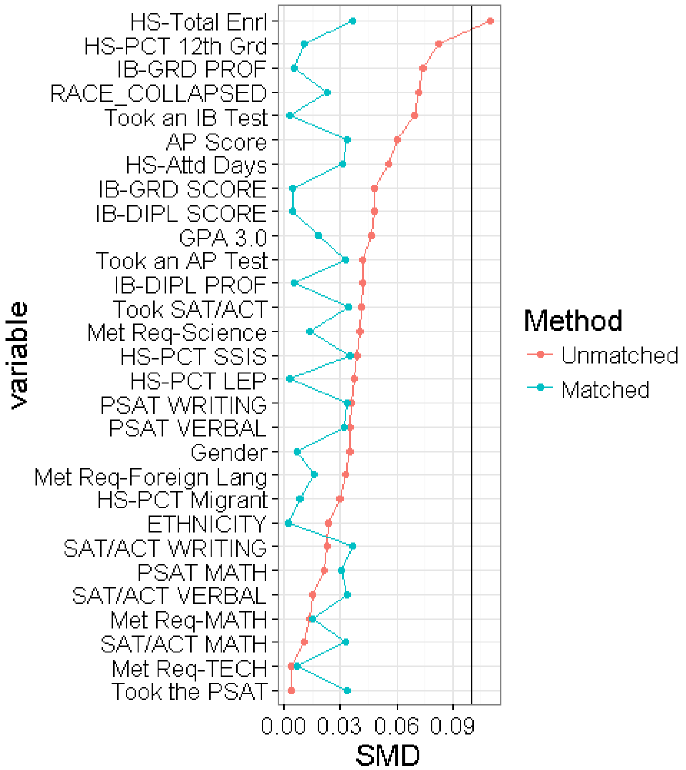


Figure C.2 shows the standardized mean differences (SMD) for the variables before and after matching. The only SMD that exceeded 0.1, the threshold taken to indicate that a difference between groups is negligible (Austin, 2011; Normand et al., 2001), was the enrollment count of the high schools the students attended. After matching, the SMD for this and all the variables was well below 0.1. This indicates that the propensity score matching procedure was successful in minimizing differences between the treatment and non-treatment groups.

Logistic regression was used to examine the effect of the treatment (going to an out-of-state 4-year college on the outcome (working in Maryland). This model was fit for each of the twenty datasets of matched pairs generated by the multiple imputations. The model

Figure C.2. Standardized Mean Differences for Variables Included in Propensity Score Model



coefficients and variances were combined across all sets of results to produce one overall set of results.

Although propensity score matching is a useful approach to minimize differences between a treatment and non-treatment group using observational data, it has some limitations (Sainani, 2012). In any propensity score matching procedure, the propensity scores generated are based on a model that predicts membership in the treatment group using a set of covariates. It is always possible that other variables that differ between the two groups are not captured in the propensity model, and that it is these variables, rather than the treatment, that lead to the relationship between the treatment and outcome. Although we included a wide range of demographic and academic achievement variables, and high school characteristics in our propensity model, other potentially pertinent information like parents' socio-economic status or number of siblings was not available. It is possible that this information would have changed the propensity model, and the relationship between going to an out-of-state college and joining the Maryland workforce may have been altered as a result. In propensity score matching, it is also possible that the matching procedure could fail to find a match for a substantial number of individuals in the treatment group, resulting in their exclusion from the outcome analysis and potentially misleading results. In our study, the matching procedure retained ~89% of students in the treatment group for the outcome analysis, mitigating concerns on this point.

Appendix D: High School Variable Summaries by Enrollment Location

High School Variables for Maryland Public High School Graduates who Enrolled In 4-Year Colleges Outside and Inside of Maryland		
	Outside Maryland (*N* = 8,145)	Inside Maryland (*N* = 8,790)
Local School System of High School:		
a	1%	1%
b	7%	7%
c	10%	14%
d	3%	2%
e	0%	1%
f	4%	4%
g	1%	1%
h	4%	3%
i	0%	0%
j	6%	5%
k	0%	0%
l	4%	3%
m	10%	10%
n	0%	0%
o	28%	21%
p	13%	13%
q	1%	1%
r	1%	1%
s	0%	0%
t	0%	0%
u	1%	1%
v	1%	1%
w	1%	1%
x	3%	8%
School Type:		
High	98%	95%
Combine	0%	1%
Vocational/Technical	2%	3%
Alternative	0%	0%
Charter	0%	0%
HS Adequate Yearly Progress Status Code:		
0	7%	9%
1	93%	91%
'Missing'	0%	0%
Free and Reduced Meals Student Count:	301.48 (252.64)	337.22 (255.19)
Special Education Student Count:	140.94 (62.37)	135.98 (64.35)
Migrant Student Count:	0.02 (0.29)	0.03 (0.31)

ESL/LEP Student Count:	43.03 (69.01)	40.16 (71.62)
Total Enrollment:	1652.76 (514.25)	1594.72 (542.37)
Grade 12 Enrollment:	386.67 (120.01)	371.19 (128.03)
School Open Days	179.85 (0.79)	179.88 (0.46)
School Open Days Through March 15:	122.35 (5.09)	122.86 (5.56)
Percent Free and Reduced Meal Students:	19%	23%
Percent Special Education Students:	9%	9%
Percent Migrant Students:	< 1%	< 1%
Percent ESL/LEP Students:	2%	2%
Percent Grade 12 of Total Enrollment:	24%	23%
NCES Program Type:		
Regular School	98%	96%
Vocational Education School	2%	3%
Alternative Education School	0%	0%
'Missing'	0%	0%
Magnet School Status:		
School-wide Magnet	1%	2%
Targeted Magnet	13%	13%
Non-magnet	86%	85%

Notes: Students whose data were included in analyses graduated from a Maryland public HS in 2009, enrolled at a 4-year college in 2010, and were not enrolled in any undergraduate program in 2016.

Appendix E: Worker Variable Summaries by Enrollment Location

Demographic, Achievement, College Attendance, and Degree Characteristics of Maryland Public High School Graduates who Worked in Maryland after College by College Location

	Workers Who Enrolled Outside Maryland for College (*N* >= 4,109)*	Workers Who Enrolled In Maryland for College (*N* >= 5,807)*
Count of college enrollment terms	*M* = 8.8*; SD* = 3.2	*M* = 8.8*; SD* = 2.8
Enrolled in a graduate program	21%	26%
Received a certificate	1%	2%
Received an associate degree	3%	2%
Received a bachelor's degree	69%	77%
Received a master's degree	3%	6%
Female	57%	57%
Under-represented minority	35%	32%
Hispanic or Latino	3%	3%
Highest AP Test Score	*M* = 3.2*; SD* = 1.4	*M* = 3.4*; SD* = 1.4
Highest IB Diploma Test Score	*M* = 17.2*; SD* = 14.0	*M* = 17.8*; SD* = 13.5
Highest IB Grade Test Score	*M* = 17.2*; SD* = 14.0	*M* = 17.8*; SD* = 13.5
Highest IB Diploma Proficiency	*M* = 2.2*; SD* = 1.9	*M* = 2.3*; SD* = 1.8
Highest IB Grade Proficiency	*M* = 4.9*; SD* = 1.3	*M* = 5.2*; SD* = 1.1
PSAT Verbal	*M* = 48.9*; SD* = 10.8	*M* = 50.5*; SD* = 10.1
PSAT Writing	*M* = 48.5*; SD* = 11.0	*M* = 50.1*; SD* = 10.3
PSAT Math	*M* = 50.3*; SD* = 11.4	*M* = 51.9*; SD* = 11.0
Took the ACT/SAT	92%	94%
Took at least one IB exam	3%	3%
Took the PSAT	80%	82%
Took at least one AP exam	63%	69%
SAT/ACT Math	*M* = 525.9*; SD* = 112.4	*M* = 542.0*; SD* = 110.7
SAT/ACT Verbal	*M* = 517.18*; SD* = 106.4	*M* = 533.4*; SD* = 100.9
SAT/ACT Writing	*M* = 515.76*; SD* = 107.8	*M* = 531.8*; SD* = 101.1
Met Rigorous HS Program Requirements for:		
Foreign Language	69%	72%
Math	57%	61%
Science	34%	37%
Advanced Technology Education	8%	8%
Completed HS with a cumulative GPA ≥ 3.0	64%	70%

Notes: These analyses include all individuals in the matched datasets with work records in Maryland after college; sample sizes shown are the minimum of the range across sets of matched data. AP= Advanced Placement, IB= International Baccalaureate, HS=high school, GPA= Grade Point Average.
Where available, ACT Reading and ACT English scores are summed, then converted into SAT Verbal scores.
* The sample sizes shown are the minimum across the matched datasets.