# Can Online Delivery Increase Access to Education?

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Most research on online education compares student performance across online and in-person formats. We provide the first evidence that online education affects the number of people pursuing education by studying Georgia Tech's Online MS in Computer Science, the earliest model offering a highly ranked degree at low cost. A regression discontinuity in admission shows that program access substantially increases overall educational enrollment. By satisfying large, previously unmet demand for midcareer training, this program will boost annual production of American computer science master's degrees by at least 7%. Online options may open opportunities for populations who would not otherwise pursue education.

## I. Introduction

Online coursework has been heralded as potentially transformative for higher education, possibly lowering costs of delivery and increasing access

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for disadvantaged students. From 2002 through 2012, the number of online bachelor's degrees awarded rose from 4,000 to 75,000, or 5% of all US bachelor's degrees issued that year (Deming et al. 2015). The federal government estimates that 27% of college students were taking at least one course online as of 2013, the most recent year for which data exist.[1] Though online education is increasingly prevalent, we know relatively little about the longer-run implications of the existence of this new form of human capital development (McPherson and Bacow 2015).

This paper provides the first evidence on whether online education can improve access to education, a key question in evaluating online education's overall impact. Does online education simply substitute for in-person education or can it instead expand access to students who would not otherwise have enrolled in an educational program? Existing research largely compares student performance in online and in-person classes, often by randomly assigning students to one format or the other conditional on already having enrolled. The online format generally leads to worse learning outcomes (Joyce et al. 2015; Alpert, Couch, and Harmon 2016; Krieg and Henson 2016), particularly for academically weaker students, such as those in community colleges (Xu and Jaggars 2014) and for-profit colleges (Bettinger et al. 2017). In some settings, students do equally well across both formats, raising the possibility that the online format may nonetheless be a cost-effective delivery mechanism (Figlio, Rush, and Yin 2013; Bowen et al. 2014).

Though the body of research on the pedagogical efficacy of the online format is growing, no prior research on online education has addressed whether the existence of online options increases the number of people obtaining education. This is in part because the ubiquity of such options makes it difficult to construct convincing counterfactuals. Understanding the impact of online education, however, depends on whether online classes replace in-person classes or generate additional human capital investment.

We provide evidence on this by examining the earliest educational model to combine the inexpensive nature of online education with a degree program from a highly ranked institution. Specifically, we study the new Online Master of Science in Computer Science (OMSCS) offered by the Georgia Institute of Technology (Georgia Tech) and developed in partnership with Udacity and AT&T. In spring 2014, Georgia Tech's Computer Science Department, which is regularly ranked in the top 10 in the United States, started

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[1] See table 311.15 of the 2014 Digest of Education Statistics, published by the US Department of Education's National Center for Education Statistics.

enrolling students in a fully online version of its highly regarded master's degree. The online degree costs about $7,000, less than one-sixth of the $45,000 that out-of-state students pay for Georgia Tech's in-person computer science master's degree (MSCS). Program price and admissions criteria were set in part to attract a much larger number of students than the in-person program without compromising the quality of the degree.

Importantly, the degree that OMSCS students earn is not labeled "online" and is in name fully equivalent to the in-person degree. As a result, the reputation and labor market value of Georgia Tech's in-person degree now at least partially depend on the extent to which Georgia Tech can ensure that the quality of its graduates does not differ substantially across the two formats. In an attempt to address the quality concerns that online education raises, Georgia Tech designed OMSCS such that its courses are online versions of the same courses that in-person students take, designed by the same faculty teaching those courses and graded using the same standards.

We first document where demand for this model of online education comes from by comparing the online and in-person applicant pools, as both programs lead to the same degree but through different formats. We find large demand for the online program, which is now the nation's largest master's degree program in computer science. Importantly, there is nearly no overlap between the applicant pools for these two programs, with few individuals applying to both. The average in-person applicant is a 24-year-old non-American recently out of college, whereas the average online applicant is a 34-year-old midcareer American. Eighty percent of those admitted to the online program accept those offers and enroll, suggesting that few find compelling alternative educational options. Large demand from a midcareer population uninterested in its in-person equivalent and a high matriculation rate both suggest that the online program is drawing in students who would not otherwise enroll elsewhere.

Next, we rigorously estimate whether this online option expands access to education for students who would not otherwise enroll, thus increasing the number of students participating in higher education. To do so, we utilize quasi-random variation in admission to OMSCS to determine the extent to which access to the online option substitutes for enrollment in other programs. We exploit the fact that capacity constraints for the first applicant cohort led to the program's admission officer reading applications in descending order of undergraduate grade point average (GPA) until he had identified about 500 applicants to which immediate admission was offered. As a result, such offers were made only to those with a GPA of at least 3.26, a threshold that was arbitrary and unknown to applicants. The officer eventually read all of the applications, and some of those below the threshold were offered deferred admission. A regression discontinuity design shows that this admissions process created at the threshold a roughly 20 percentage point difference in the probability of admission to the online program.

With National Student Clearinghouse (NSC) data that track enrollment in any US formal higher education, we use a regression discontinuity design to compare enrollment outcomes for applicants just above and just below that threshold, two groups who differ only in their access to this online option. We find a roughly 20 percentage point difference in the probability of eventually enrolling in the online program, the magnitude of which suggests that roughly all of the marginal admits ultimately matriculate.[2] Importantly, we show that very few applicants to OMSCS enroll in other, non-OMSCS programs. Those just below the admission threshold are no more likely to enroll elsewhere than those just above it, implying that access to the online program does not substitute for other educational options. Such access thus substantially increases the number of students enrolling at all. The higher education market appears to have been failing to meet demand for this online option.

To assess whether OMSCS substituted for informal educational options, such as massive online open courses (MOOCs) or professional certification programs, we surveyed applicants to the first OMSCS cohort 3.5 years after the start of the program. While almost three-quarters of applicants had undertaken informal training in the interim, the average time spent in nondegree training was small relative to the time a degree program requires. Using our regression discontinuity design, we find no evidence that OMSCS substituted for nondegree options. Combining time spent on formal and informal education, we find that access to OMSCS had a large and significant impact on total training.

Early evidence also suggests that this online program is delivering a relatively high-quality educational experience. To test whether students pursuing the degree online were finishing their courses with as much knowledge as those pursuing it in person, Georgia Tech blindly graded final exams for online and in-person students taking the same course from the same instructor. The online students slightly outperformed the in-person students (Goel and Joyner 2016).[3] OMSCS students are also persisting at rates substantially higher than students in nearly all MOOCs and higher than in many online degree programs. Among those students who started OMSCS in 2014, 62% remained enrolled 2 years later, apparently on track to complete their degrees. This is very likely a lower bound on completion rates given that over 25% of students who take a semester off from the program reenroll in sub-

[2] The difference in OMSCS enrollment at the discontinuity is not due to differential likelihood of enrolling in OMSCS conditional on admission. On both sides of the discontinuity, 80% of admitted students enroll in the program.

[3] We lack baseline measures of student skill that would allow us to distinguish the hypothesis that online delivery was as pedagogically effective as in-person delivery from the hypothesis that online students started from a higher knowledge base than in-person students. We also lack data that would allow us to determine OMSCS's impact on earnings and other labor market outcomes.

sequent semesters. Given the nearly 1,200 Americans enrolling in OMSCS each year and assuming only those 62% graduate, this implies production of at least 725 new American computer science master's degree holders annually. Roughly 11,000 Americans earn their master's degree in computer science each year, implying that this single program will boost annual national production of American computer science master's degrees by about 7%.

The fact that OMSCS appears to be filling a gap in the higher education market may explain why the announcement of the program in 2013 garnered such extensive media attention. OMSCS was described as the first large-scale program offered by a highly ranked department, priced much lower than its in-person equivalent and culminating in a prestigious graduate degree. Prior models of online education had involved highly ranked institutions offering online degrees as costly as their in-person equivalents, lower-ranked institutions offering inexpensive degrees with low labor market returns (Deming et al. 2016), or free MOOCs with unclear returns and very high attrition rates (Perna et al. 2013; Banerjee and Duflo 2014). Because OMSCS's price-quality pairing had not been previously seen in online education, the *New York Times* declared that this model meant "disruption may be approaching" (Lewin 2013). President Obama mentioned OMSCS in an August 2013 speech on college affordability and again in March 2015 while visiting Georgia Tech, describing the program as a model for "innovative ways to increase value" in higher education (Obama 2015).

Features of OMSCS made possible only by online technology appear central to demand for this educational option. We surveyed OMSCS applicants about the program features that were most important in their decision to apply. The four most important options all related to geographic and temporal flexibility: the lack of need to commute or relocate, the flexibility of coursework and time commitments, and general convenience. We view this extreme flexibility as unique to online education. Asynchronous online education allows students to learn material and complete assignments on a schedule they can customize around their family- and job-related time constraints. Distance learning allows students to access education without the need to commute or relocate themselves or their families. Many applicants also valued OMSCS's low cost, though fewer than those that valued its flexibility. While lower costs are not a feature of all online education, economies of scale allow online classes to cost less per student. Unlimited by geography, scheduling, or classroom size, online classes can be much larger than in-person classes. Moreover, while there are large up-front costs of creating online content, such content can be reused so that cost is spread over even more students.

Online models combining a low cost with a credential from a highly ranked university appear to be growing in importance. In spring of 2016, inspired in part by OMSCS, the University of Illinois at Urbana-Champaign (UIUC) began enrolling students in its "iMBA" program, a fully online version of its highly regarded master of business administration (MBA). The degree costs about $22,000, roughly one-third the cost of the in-person MBA offered by UIUC and similarly ranked institutions. UIUC also has a new online master's program in data science that will cost just over $19,000. Yale University is currently developing a fully online version of its master of medical science degree for physician assistants. In the fall of 2016, over a dozen highly ranked universities affiliated with the edX consortium started by Harvard and Massachusetts Institute of Technology (MIT) announced plans to offer micromaster's degrees. Such degrees will be open to any student willing to pay a total of roughly $1,000 for exam proctoring at the end of each course and will consist of between one-quarter and one-half of the courses in a traditional version of each degree. Examples of such degrees include supply chain management from MIT, artificial intelligence from Columbia University, and social work from the University of Michigan at Ann Arbor (Young 2016). The fact that more highly ranked institutions appear to be entering the market for inexpensive online degrees suggests that our results may be increasingly relevant to the future of online education.

The remainder of the paper proceeds as follows. In Section II, we describe the OMSCS program in more detail, the available data, and our survey, while in Section III we present descriptive statistics on applicants to the in-person and online programs. We present regression discontinuity estimates of the impact of access to online education on formal and informal enrollment in Section IV. Finally, in Section V we discuss the implications of our findings. We argue that the single program studied here will likely increase the number of Americans earning computer science master's degrees by about 7%. We also discuss the external validity of these findings as well as concerns about the quality of education delivered by the online program.

## II. Context and Data

### A. OMSCS Degree Program

OMSCS courses are offered through a platform designed by Udacity, one of the largest providers of MOOCs.[4] To earn their degree, OMSCS students must complete 10 courses, specializing in either computational perception and robotics, computing systems, interactive intelligence, or machine learning. Students who have taken two foundational courses can take up to three classes per semester, while other students can take only two at a time. The typical student takes one or two courses each semester, so that expected time to graduation is six or seven semesters, which can include summer terms. To maintain educational quality, the online courses use similar assignments and grading standards as their in-person counterparts. Consistent with the OMSCS degree being at least nominally equivalent to the MSCS degree,

[4] To create the OMSCS program, Georgia Tech partnered with Udacity and AT&T, the latter of which provided start-up funding.

OMSCS is accredited because the accreditor considers it equivalent to the in-person program.

Though deadlines for submitting assignments are the same as for the in-person courses, one major difference is that all lecture watching and other learning experiences are asynchronous, meaning that there is no fixed time during which a student must be online. All content is posted at the start of the semester so that students may proceed at a pace of their choosing. Students schedule their exams within a specified window and are monitored to guard against cheating. Most interaction happens in online forums where students post questions and receive answers from fellow students, teaching assistants, or faculty members. Faculty members interact with students in online office hours, though online forums are typically run by the head teaching assistant. Feedback on assignments comes from teaching assistants, many of whom are current MSCS or OMSCS students and each of whom serves approximately 50 students.[5]

AT&T provided roughly $4,000,000 in start-up funds to supplement Georgia Tech's own initial investment. Much of that funded production of the roughly 30 courses OMSCS offers, each of which initially costs about $300,000 to produce, though production costs have since dropped to under $200,000. Such costs reflect the fact that OMSCS does not record and rebroadcast in-person lectures as some online courses do but instead produces original videos and other material for each course. Individual faculty members are paid $20,000 for initially creating a course and $10,000 each time they teach the course, which many of them continue to do. In 2015, OMSCS had net revenues of about $2,000,000 and by fall 2016 had returned the Computer Science Department's initial investment in the program.

To make OMSCS accessible to a wider range of applicants than its in-person counterpart, its admissions website describes having a bachelor's degree in computer science or a related field with an undergraduate GPA of 3.0 or higher as "preferred qualifications."[6] Such qualifications do not guarantee admission, and as the website notes, "applicants who do not meet these criteria will be evaluated on a case-by-case basis." The admissions website to the in-person program describes a GPA of 3.0 as a "desirable minimum" and notes that "most candidates score higher." MSCS also requires submission of graduate record examination (GRE) scores, which OMSCS does not. Whereas MSCS has one cohort of applicants each year who apply to start in

[5] One teaching assistant is not human. Professor Ashok Goel, who teaches a course entitled "Knowledge-Based Artificial Intelligence," created a virtual teaching assistant named Jill, based on artificial intelligence technologies adapted from IBM's Watson platform. Jill regularly answered students' questions and was revealed to them as virtual only late in the semester.

[6] As we describe below, our regression discontinuity analysis uses a different GPA cutoff that affected the probability of admission but was unknown to applicants.

the fall, OMSCS has two applicant cohorts each year, as students can begin their coursework in either the fall or the spring. The first OMSCS enrollees began their coursework in the spring of 2014.

### B. Data

We have data from Georgia Tech's Computer Science Department on all applicants to OMSCS's first six cohorts, who started their courses in spring and fall of 2014, 2015, and 2016. We also have data on four cohorts of applicants to MSCS, those applying to start classes in each fall from 2013 through 2016. For each applicant, we have basic self-reported demographic information including age, gender, race/ethnicity, and citizenship. Applicants also report their postsecondary-educational history, including the name of each college attended, their GPA at that college, and the field and type of any degree earned. Applicants report the name of their employer if employed at the time of application. We also observe whether a given applicant was ever admitted to or enrolled in OMSCS or MSCS.

We merge all applicants' data to the NSC, an organization that tracks enrollment at postsecondary institutions throughout the United States. The NSC identifies which, if any, institution a student is enrolled in at any moment in time, allowing us to track the educational trajectories of students who enroll in Georgia Tech and other institutions.[7] NSC coverage rates for undergraduates in Georgia are around 95% and generally above 90% in other states (Dynarski, Hemelt, and Hyman 2015). Though less is known about graduate student coverage rates, we show that a very high fraction of MSCS applicants are observed enrolling in institutions other than Georgia Tech, suggesting widespread coverage of master's degree students. Importantly, we do observe many for-profit and nonprofit institutions that primarily offer online coursework, such as the University of Phoenix and Western Governor's University. We supplement this with data from the National Science Foundation (NSF) on the full population of students earning computer science master's degrees in the United States in 2013, the most recent year available.

Because the NSC data contain information only on enrollment in formal higher education degree programs, we conducted an online survey on other forms of training that would not be captured by such data. The survey was sent in July 2017 by email to all spring 2014 OMSCS applicants, asking them about their experiences from the time they first applied to OMSCS. Respondents were asked whether since January 2014 they had participated in any form of training in computing or computer science that was not part of a formal graduate degree program and, if so, how many hours they had spent on such training. They were given the option to indicate participation in professional certification programs (such as Microsoft Certifications), coding

[7] Though the NSC also records degree completion, it is too early to measure this.

boot camps (such as General Assembly), MOOCs, and other forms of training that they could specify. Respondents indicating that they were employed in January 2014 were asked whether that employer would have been willing to subsidize participation in OMSCS, other graduate degree programs, and training not leading to a graduate degree. Finally, respondents were asked to indicate how important various OMSCS characteristics were in their decision to apply.[8]

## III. Descriptive Comparison of Applicant Pools

To document where demand for OMSCS comes from, we describe the characteristics of the OMSCS applicant pool and compare them to the characteristics of the MSCS applicant pool. Because both programs culminate in the same nominal degree, we view such a comparison as controlling for the degree sought. As such, we argue that differences in the applicant pools between these programs are largely due to differences in the programs' costs and methods of curriculum delivery.

Demand for the online program is large, as seen in panel A of table 1. OMSCS attracts over 3,400 applicants annually, about twice as many as its in-person equivalent. This is not due simply to large pent-up demand, as the most recent applicant cohort is larger than all but the first cohort, which contained many AT&T employees.[9] OMSCS admits 61% of those applicants, almost five times the 13% admission rate for the in-person program. OMSCS is thus less selective and more open than its in-person counterpart, as program designers intended.

Eighty percent of those admitted to the online program enroll, so that each year nearly 1,700 students begin a computer science master's degree through OMSCS, more than 10 times as many as who begin a degree through MSCS. This makes OMSCS the largest computer science master's degree program in the United States and possibly the world. By way of comparison, the NSF estimates that US institutions issued about 21,000 computer science master's degrees in 2013. If all OMSCS enrollees were to complete their degrees, OMSCS would be responsible for the production of 8% of all computer science master's degrees in the country. The nearly 1,200 annual American enrollees in OMSCS would represent over 10% of all Americans earning such degrees.

Two descriptive facts suggest that demand for the online program comes from a different population than demand for the in-person program. First, in our data, fewer than 0.2% of the nearly 18,000 applicants to either program applied to both programs, suggesting that students view these programs as distinct educational products. Second, as panel B in table 1 shows, the ap-

[8] For specific wording of the survey questions, see the appendix, available online.
[9] See cols. 1–6 of table A1 (tables A1–A4 are available online).

**Table 1**
**Characteristics of Program Applicants and Enrollees**

| | All | | | US | | |
|---|---|---|---|---|---|---|
| | Online (1) | In Person (2) | NSF (3) | Online (4) | In Person (5) | NSF (6) |
| A. Application and enrollment: | | | | | | |
| Degrees awarded | | | 20,983 | | | 10,948 |
| Number applied (annualized) | 3,410 | 1,851 | | 2,407 | 141 | |
| Number admitted (annualized) | 2,075 | 233 | | 1,462 | 68 | |
| Number enrolled (annualized) | 1,663 | 120 | | 1,169 | 33 | |
| Admission rate | .61 | .13 | | .61 | .48 | |
| Enrollment rate | .49 | .06 | | .49 | .24 | |
| B. Applicant characteristics: | | | | | | |
| US citizen | .71 | .08 | | | | |
| Age | 33.8 | 23.9 | | 34.7 | 25.1 | |
| Employed | .87 | .49 | | .90 | .41 | |
| White | .50 | .06 | | .64 | .54 | |
| Black or Hispanic | .16 | .02 | | .17 | .15 | |
| Asian | .31 | .91 | | .15 | .27 | |
| Female | .15 | .25 | | .13 | .17 | |
| Computer science major | .37 | .63 | | .40 | .52 | |
| C. Enrollee characteristics: | | | | | | |
| US citizen | .70 | .28 | .52 | | | |
| Age | 32.4 | 24.1 | | 33.0 | 25.8 | |
| Employed | .89 | .42 | | .92 | .41 | |
| White | .51 | .23 | | .67 | .61 | .54 |
| Black or Hispanic | .12 | .06 | | .12 | .14 | .18 |
| Asian | .33 | .70 | | .17 | .20 | .14 |
| Female | .13 | .30 | .27 | .11 | .17 | .26 |
| Computer science major | .42 | .62 | | .46 | .56 | |

NOTE.—Data in cols. 1 and 4 come from all 2014–16 online program applicants. Data in cols. 2 and 5 come from all 2013–16 in-person program applicants. Column 3 describes those who completed computer science master's degrees in the United States in 2013 and comes from the 2013 Integrated Postsecondary Education Data System Completion Survey, accessed through the National Science Foundation's (NSF) WebCASPAR site. Columns 1–3 include all individuals, while cols. 4–6 limit the sample to American citizens. For comparability, the numbers in cols. 1, 2, 4, and 5 of panel A are scaled to be annual. In panel A, the enrollment rate is calculated as the fraction of applicants who enrolled.

plicant pools to the two programs look very different, particularly in terms of nationality and age.[10]

The online program attracts a much more American demographic than does the in-person program. About 70% of the online applicants are US citizens, compared to 8% of in-person applicants. Figure 1 shows the distribution of citizenship across the two pools. The vast majority of in-person applicants are citizens of India (nearly 70%) or China (nearly 20%). After

[10] Table A1 shows the characteristics of individual cohorts of applicants. None of the demographic facts highlighted here changes substantially over the observed time period.

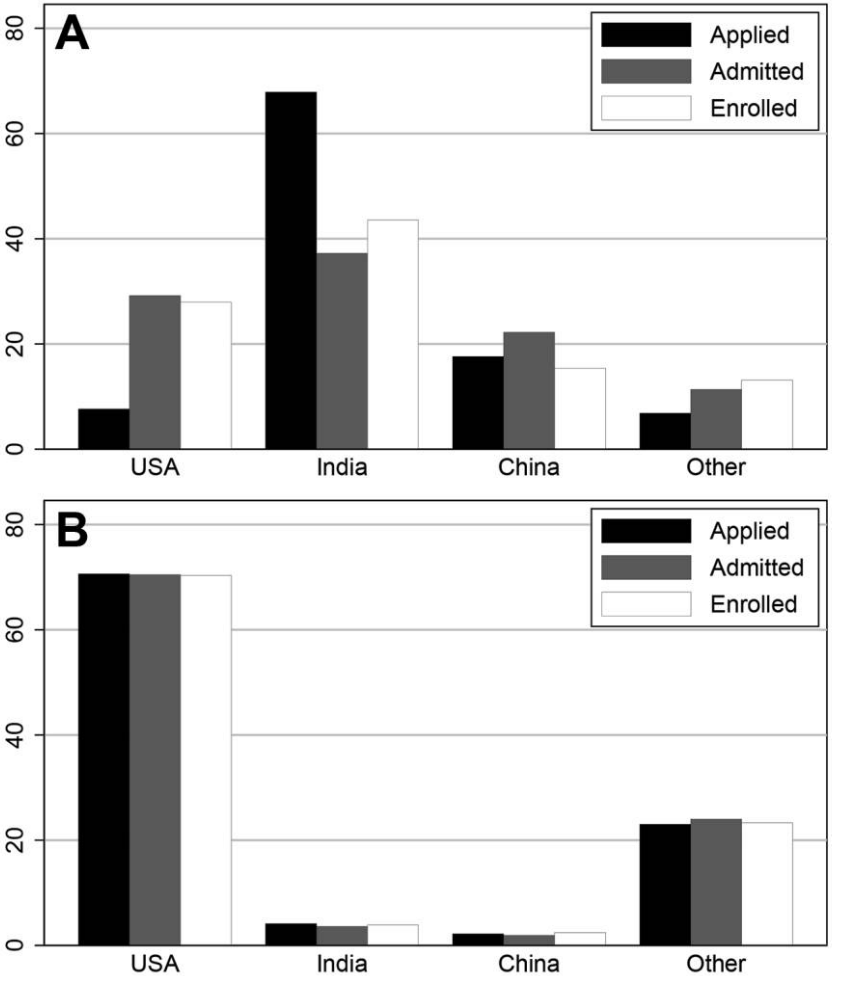


FIG. 1.—Citizenship of in-person and online program applicants. *A*, In-person program applicants. *B*, Online program applicants. *A* and *B* show the distribution of citizenship of applicants to the in-person and online programs, respectively. *A* includes all 2013–16 in-person program applicants. *B* includes all 2014–16 online program applicants. From left to right, the three bars show the fraction of applicants, admitted students, and enrolled students from each country.

admissions and enrollment decisions, the fraction of in-person enrollees who are US citizens rises to 26%. Even so, over half of that student body are Indian or Chinese citizens. Panel B shows that fewer than 10% of applicants to the online program are Indian or Chinese citizens, proportions that do not substantially change with admissions and enrollment decisions. That international applicants show stronger demand for the in-person program suggests that such students may value the opportunity to be physically present in the United States, which admission to an online program does not grant.[11] That over 70% of online program enrollees are US citizens makes that pool substantially more American than the national pool of those completing computer science master's degrees, of whom 52% are US citizens.

The online program attracts a substantially older demographic than does the in-person program. Online applicants are on average 34 years old, compared to an average age of 24 for in-person applicants. Figure 2 shows the age distribution of applicants to the two programs. Over 75% of in-person applicants are 25 years old or younger, and over 95% are 30 or younger. Nearly no one older than 30 applies to the in-person program. The opposite is true of the online program. Only 10% of online applicants are 25 or younger, and fewer than 30% are between 25 and 30. The majority of applicants are over 30 years old, with substantial representation of those in their forties and fifties. This remains true if the sample is limited to those admitted or to those who enroll.

Whereas the in-person program attracts applicants straight out of college or early in their careers, the online program attracts an older population largely in the middle of their careers. Nearly 90% of online applicants list a current employer, relative to under 50% of in-person applicants.[12] Table 2 shows more detail about online applicants' employment, listing the top 25 employers represented in their applications. Because of its corporate sponsorship of the development of OMSCS, AT&T is by far the largest such employer.[13] Well represented in the list are technology giants (Microsoft, Google, Amazon, Apple), military branches (Air Force, Army, Navy), defense contractors (Lockheed Martin, Raytheon, Northrop Grumman, Boeing), and financial and consulting firms (Bank of America, Accenture). Such firms, with more than 25 employees applying to OMSCS, comprise less than one-quarter of the applicant pool. Firms with two to 25 applicants comprise one-fifth of the applicant pool. Remarkably, nearly half of applicants to OMSCS appear to be the only employee from their firms applying to the program, suggesting that demand for such training is widespread and not simply concentrated among a few large firms.

[11] Low international awareness of OMSCS's existence may explain a small portion of their proportionally stronger demand for the in-person program, as table A1 shows that the international composition of the applicant pool has very slowly increased over time, perhaps because such awareness has increased.

[12] Employment information is missing for the 2013 MSCS applicants, so the 50% figure is based on 2014–16 MSCS applicants.

[13] As seen in table A1, this is largely driven by the first cohort of applicants, of whom 23% were from AT&T. That proportion drops to fewer than 10% in subsequent cohorts. None of the demographic facts discussed here changes meaningfully when AT&T employees are removed from the sample.

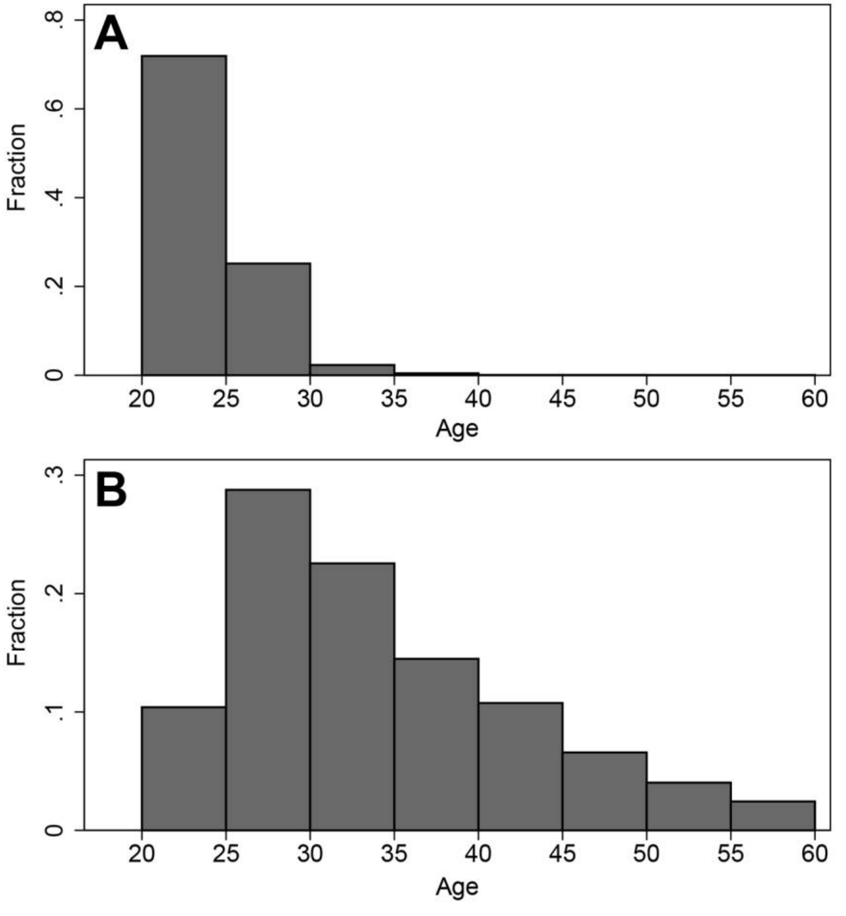


FIG. 2.—Age distribution of in-person and online program applicants. *A*, In-person program applicants. *B*, Online program applicants. *A* and *B* show the age distribution of applicants to the in-person and online programs, respectively. *A* includes all 2013–16 in-person program applicants. *B* includes all 2014–16 online program applicants. The 75 applicants with ages below 20 or above 60 are rounded to those values for this figure.

The online and in-person applicant and enrollee pools look fairly similar in terms of gender and race, particularly when the sample is limited to US citizens. Only 13% of US citizen online applicants are female, a proportion quite similar to the percentage in the in-person program.[14] Among US citizens, the online applicant pool is 64% white, 17% black or Hispanic, and

[14] Among all applicants, the in-person program has a higher proportion of female applicants due to the fact that Indian and Chinese applicants are more likely to be female than are American applicants.

**Table 2**
**Distribution of Employers for Online Program Applicants**

| Listed employer | Number of Applicants | Percentage of Total | Cumulative Percentage |
|---|---|---|---|
| AT&T | 1,062 | 10.44 | 10.44 |
| Microsoft | 105 | 1.03 | 11.47 |
| Intel | 99 | .97 | 12.44 |
| IBM | 94 | .92 | 13.36 |
| US Air Force | 90 | .88 | 14.24 |
| Google | 78 | .77 | 15.01 |
| US Army | 68 | .67 | 15.68 |
| United Parcel Service | 66 | .65 | 16.33 |
| Lockheed Martin | 63 | .62 | 16.95 |
| Amazon | 59 | .58 | 17.53 |
| Cisco Systems | 58 | .57 | 18.10 |
| Oracle | 56 | .55 | 18.65 |
| General Motors | 51 | .50 | 19.15 |
| Boeing | 47 | .46 | 19.61 |
| General Electric | 47 | .46 | 20.07 |
| Raytheon | 46 | .45 | 20.52 |
| Northrop Grumman | 43 | .42 | 20.94 |
| Hewlett-Packard | 40 | .39 | 21.33 |
| Accenture | 39 | .38 | 21.71 |
| Apple | 33 | .32 | 22.03 |
| Bank of America | 31 | .30 | 22.33 |
| JPMorgan Chase | 29 | .29 | 22.62 |
| US Navy | 28 | .28 | 22.90 |
| Booz Allen Hamilton | 26 | .26 | 23.16 |
| Capital One | 26 | .26 | 23.42 |
| Employers with two to 25 applicants | 1,930 | 18.97 | 42.39 |
| Employers with one applicant | 4,473 | 43.97 | 86.36 |
| No employer listed | 1,385 | 13.62 | 100.00 |

NOTE.—Shown above are the top 25 employers listed by all 2014–16 online program applicants as well as the total number of applicants from employers with two to 25 applicants, from employers with only one applicant, and with no employer listed.

15% Asian, proportions roughly similar to the in-person applicant pool. There is little evidence of differential gender or racial diversity by program type. Other forms of diversity, such as socioeconomic status and academic skill, are hard to evaluate because our application data contain no information on family background and no objective measures of academic skill that are comparable across the two applicant pools.[15]

We can, however, use characteristics of applicants' undergraduate institutions as proxies for applicants' family backgrounds and academic skills. To do so, we use data from the Integrated Postsecondary Education Data Sys-

[15] Unlike the in-person program, the online program does not require applicants to submit GRE scores.

tem (IPEDS) to characterize applicants by the US colleges they attended.[16] Table 3 shows clear differences across the two applicant pools. Online applicants come from colleges where the average student's SAT math score is 30 points, or about 0.2 standard deviations, lower than students from in-person applicants' colleges. Online applicants' colleges have a higher proportion of low-income students, as well as a substantially lower 6-year graduation rate. Differences among admitted students and enrollees are of similar magnitude. This suggests that the online program attracts applicants who are from more economically disadvantaged backgrounds and who are academically weaker on average than their in-person counterparts. Online applicants also have a more diverse set of college majors, as they are much less likely than in-person applicants to have majored in computer science. Instead, they are more likely to have majored in engineering, mathematics, physical sciences, and even social sciences and humanities.

Our online survey of spring 2014 OMSCS applicants reveals preferences consistent with the appeal of online education to those whose jobs, families, or residential situations do not allow for enrollment in traditional programs. Table 4 shows that the survey had a 38% response rate.[17] The survey, presented in the appendix, listed a number of features of the OMSCS program. For each, respondents were asked to rate its importance in their decision to apply to OMSCS. Panel B lists program characteristics in descending order of the fraction of respondents describing the given characteristic as "extremely important." The top four characteristics all relate to the geographic or temporal flexibility that an asynchronous, fully online program provides, with 69% valuing the lack of need to commute or relocate to attend and 65% valuing the program's flexible time commitments.[18] The cost and Georgia Tech's reputation are the next most valued characteristics, with 53% of respondents citing them as extremely important and 85%–90% citing them as important or extremely important. Skill development was cited as extremely

[16] We use IPEDS data from 2005, roughly the average year of college graduation for online applicants. Our results are not sensitive to this choice given how slowly college characteristics change over time. We are able to link 67% of OMSCS applicants and 11% of MSCS applicants to colleges in IPEDS. For both programs, we can link 88% of US citizen applicants to their colleges.

[17] As shown in table A2, survey respondents and nonrespondents are quite similar in terms of gender, country of residence, and college major. Respondents were more likely to be white, were slightly older, and were slightly more likely to be employed than nonrespondents. Respondents overwhelmingly report having been employed in January 2014 (91%), at a rate that is nearly identical to that reported on the official applications. As fig. A1 (figs. A1–A8 are available online) shows, applicants with GPAs just above the admissions threshold were insignificantly slightly more likely to respond than those with GPAs just below the threshold.

[18] If we consider the fraction of respondents indicating that a characteristic was important or extremely important in their decision to apply, the top four characteristics are the same, with over 90% choosing each.

**Table 3**
**Applicants' Undergraduate College Characteristics**

| | Applicants | | Admits | | Enrollees | |
|---|---|---|---|---|---|---|
| | Online | In Person | Online | In Person | Online | In Person |
| SAT math score | 649 | 679 | 655 | 692 | 657 | 692 |
| Fraction low income | .23 | .20 | .22 | .17 | .22 | .17 |
| 6-year graduation rate | .61 | .70 | .62 | .73 | .63 | .71 |
| *N* | 6,882 | 800 | 4,316 | 341 | 3,449 | 170 |

NOTE.—Shown above are the means of undergraduate college characteristics for all online and in-person program applicants, admits, and enrollees, as derived from the 2005 wave of Integrated Postsecondary Education Data System (IPEDS). All differences between the two programs are statistically significant at the 1% level. The sample includes only students whose listed undergraduate colleges were found in IPEDS. SAT math scores are the 75th percentile of the incoming freshman distribution. The fraction of students classified as low income is measured by the proportion receiving federal grant aid.

important by just under half of applicants, while only 19% of applicants appear to have valued professional networks the program might impart.

Panel C shows that 63% said their employer would subsidize OMSCS, and a nearly identical proportion would have subsidized other degrees or nondegree training, suggesting that differential employer-based support of OMSCS cannot explain its appeal relative to other options. Older workers' employers are 12–15 percentage points more likely to subsidize training, the only substantial survey difference by applicant age.[19]

Participating in nondegree training is common among OMSCS applicants, but the number of hours they spend doing such training is dwarfed by the hours spent in formal degree-based programs. Panel D of table 4 shows that 72% of respondents report having participated in some type of nondegree training between January 2014, when they applied to OMSCS, and July 2017, when the survey was administered. Respondents report having spent an average of 111 hours in such nondegree training over 3.5 years, half of which comes from MOOCs.[20] To compare this to time spent in formal graduate degree programs, we use the NSC data to compute the number of semesters during which respondents were formally enrolled, assume that each semester is 13 weeks long, and take OMSCS's suggestion that the typical student will "spend roughly 18 hours per week on coursework" as our best estimate of time spent.[21] Doing so shows that the average respondent

[19] That older applicants' employers are more willing to subsidize training is fully statistically explained by the fact that older workers have larger employers. Controlling for the number of applicants from a given employer largely eliminates the raw difference observed by age in panel C.

[20] Over one-quarter of the nondegree training hours come from "other" experience. Of respondents who listed specific experiences, most appeared to be referring to informal coursework or certification.

[21] This number is taken from OMSCS's FAQ at http://www.omscs.gatech.edu/prospective-students/faq (accessed on August 10, 2017). We use OMSCS's figure because, as we show below, few applicants enroll anywhere other than OMSCS.

**Table 4**
**Online Master of Science in Computer Science (OMSCS) Applicant Survey Responses**

| | All (1) | Age ≤ 35 (2) | Age > 35 (3) |
|---|---|---|---|
| A. Response rate: | | | |
| Responded to survey | .38 | .36 | .40 |
| *N* | 2,419 | 1,218 | 1,201 |
| B. Important program features: | | | |
| No need to commute or relocate | .69 | .70 | .69 |
| Flexible time commitments | .65 | .64 | .67 |
| Convenience | .62 | .60 | .63 |
| Flexible coursework schedule | .60 | .60 | .59 |
| Cost | .53 | .54 | .51 |
| Reputation of Georgia Tech | .53 | .51 | .54 |
| Challenge, skill development | .47 | .47 | .47 |
| Professional network | .19 | .15 | .22 |
| *N* | 876 | 419 | 457 |
| C. Employer would subsidize: | | | |
| OMSCS | .63 | .55 | .70 |
| Other graduate degrees | .61 | .55 | .67 |
| Nondegree training | .59 | .52 | .65 |
| *N* | 723 | 337 | 386 |
| D. Hours of training: | | | |
| Did any type of nondegree training | .71 | .68 | .74 |
| Hours of nondegree training | 111.25 | 105.67 | 116.29 |
| Hours of MOOCs | 57.20 | 55.72 | 58.53 |
| Hours of professional certification | 16.63 | 13.60 | 19.37 |
| Hours of coding boot camp | 6.33 | 8.65 | 4.24 |
| Hours of other types | 31.09 | 27.69 | 34.15 |
| Hours of degree training (estimated) | 796.07 | 861.30 | 737.20 |
| Hours of all training (estimated) | 907.32 | 966.96 | 853.49 |
| *N* | 898 | 426 | 472 |

NOTE.—Listed above are mean values of survey responses from spring 2014 OMSCS applicants. The sample in each panel consists of respondents who gave valid answers to all questions in that panel. Panel B lists in descending order the fraction of respondents who described a given program feature as extremely important in their decision to apply to OMSCS. Panel C refers to the willingness of one's January 2014 employer to subsidize training. Panel D refers to nondegree training conducted from January 2014 through July 2017. Degree training hours are estimated from National Student Clearinghouse data by assuming that each semester enrolled requires 18 training hours per week for 13 weeks. MOOC = massive online open course.

spent nearly 800 hours on degree-based programs, so that nondegree training represents only 12% of the total time spent on training.

The descriptive comparison of the two applicant pools thus provides three pieces of evidence that together are consistent with the possibility that OMSCS represents a new educational product for which there is currently no close substitute in the higher education market. First, though the two programs culminate in the same degree, there is nearly no overlap in the populations interested in these educational options. The typical applicant to the in-person program is a 24-year-old recent college graduate from India, whereas the typical applicant to the online program is a 34-year-old currently employed American. Second, demand from Americans for the online version of the program is large, with well over 10 times more American applicants to OMSCS than to MSCS. Third, 80% of those admitted to the online program accept those offers and enroll, suggesting that relatively few such admits find alternative higher education options compelling. Survey evidence suggests both that the flexibility enabled by online technology is central to OMSCS's appeal and that nondegree training, though common, occupies much less of applicants' time than does formal graduate education. Large demand for OMSCS from a midcareer population uninterested in its in-person equivalent and the high enrollment rate among admits both suggest that OMSCS provides an educational pathway for which there has previously been no compelling, competing alternative. To strengthen the case for this argument, we turn to a second empirical strategy that focuses on causal inference and complements the descriptive analysis above.

## IV. Impact of Online Access on Educational Trajectories

### A. Regression Discontinuity Design

Our goal is to determine whether the existence of an online option alters applicants' educational trajectories. If not for access to such an option, would its applicants pursue other educational options? Or does the online option lack close substitutes in the current higher education market? The difficulty in answering this question is that applicants admitted to OMSCS are generally academically stronger than and differ along other dimensions from those denied admission. Comparing the subsequent educational trajectories of these two groups of students would confound the impact of online access with the impact of underlying academic skills and other characteristics.

We solve this problem by identifying an exogenous source of variation in the probability that an applicant had access to the online option. In particular, though OMSCS admitted a wider range of students in later cohorts, the program decided to somewhat constrain the number of students admitted to the very first cohort in spring 2014. OMSCS did this to ensure that any challenges inherent in starting a new program would not be compounded by an overly large enrollment total. The chief admissions officer therefore read applications in descending order of undergraduate GPA and offered immediate admission only to the first 500 or so applications that he deemed admissible. As a result, only applicants with an undergraduate GPA of 3.26 or higher were eligible for admission in spring 2014.

The admissions officer ultimately read all applications, and some students both below and above the 3.26 threshold were made offers of deferred admission. Such students were allowed to enroll in summer 2014, fall 2014, or spring 2015. The admissions data we have cannot distinguish between students made offers of admission for spring 2014 and those who were offered deferred admission. We therefore measure enrollment outcomes as of fall 2016, well beyond the point at which all spring 2014 applicants would have had to enroll if admitted or would have had time to apply to and enroll in other institutions if rejected. We focus on the probability that a given student received any admission offer, regardless of its timing.

The GPA threshold thus represents an exogenous source of variation in whether a given student was offered admission to OMSCS. We use the threshold to implement a regression discontinuity design that compares the educational trajectories of applicants just above and just below that threshold. Such students should be nearly identical in terms of academic skills, as measured by GPA, as well as other characteristics. They should differ only in their access to the online option. We estimate the impact of having a GPA above the admissions threshold on enrollment outcomes of the first applicant cohort through the following baseline specification:

$$\text{Enrolled}_i = \beta_0 + \beta_1\text{Admissible}_i + \beta_2\text{GPA}_i + \beta_3\text{Admissible}_i \cdot \text{GPA}_i + \epsilon_i. \tag{1}$$

Here "Enrolled" indicates enrollment status in OMSCS or other programs for applicant *i*, "Admissible" indicates that the applicant is above the GPA threshold, and "GPA" measures their distance from that threshold in GPA points. In this local linear regression, the two GPA variables model the relationship between GPA and college outcomes as linear, with the interaction term allowing that slope to vary on either side of the threshold. The coefficient on Admissible thus measures the difference in OMSCS enrollment probability between applicants just above and just below that threshold. This specification generates intent-to-treat estimates of the impact of increased access to OMSCS.

Using the same basic specification, we also generate instrumental variable estimates of the impact of admission on enrollment, where admission is instrumented with having an immediately admissible GPA. Specifically, we estimate the first-stage equation

$$\text{Admitted}_i = \alpha_0 + \alpha_1\text{Admissible}_i + \alpha_2\text{GPA}_i + \alpha_3\text{Admissible}_i \cdot \text{GPA}_i + \epsilon_i, \tag{2}$$

where "Admitted" indicates eventual admission to OMSCS. We then use predicted values of Admitted to estimate a second stage of the form

$$\text{Enrolled}_i = \gamma_0 + \gamma_1\widehat{\text{Admitted}}_i + \gamma_2\text{GPA}_i + \gamma_3\text{Admissible}_i \cdot \text{GPA}_i + \epsilon_i. \tag{3}$$

This yields estimates of the impact of OMSCS admission on enrollment choices for compliers at the margin, namely, those students for whom the threshold itself altered their probability of eventual admission. We think of this as a matriculation rate for such applicants.

Following Lee and Card (2008), our baseline specifications for all of these estimates cluster standard errors by distance from the GPA threshold because GPA is a fairly discrete variable, with many students reporting values that are multiples of 0.1 or 0.25. To improve precision, we include demographic controls for gender, race/ethnicity, citizenship, age, employment, and college major. Optimal bandwidths, as suggested by both Imbens and Kalyanaraman (2012) and Calonico, Cattaneo, and Titiunik (2014), are between 0.3 and 0.5 GPA points for all outcomes. We treat 0.5 GPA points as our default bandwidth but show that our results are robust to the use of smaller and larger bandwidths as well as to the exclusion of demographic controls.

Validity of our regression discontinuity estimates requires that students not systematically manipulate which side of the GPA threshold they fall on. Though they do self-report GPAs, two facts suggest little scope for manipulation. First, applicants were required to submit transcripts and thus knew that their self-reported GPAs might be checked against officially reported ones. Second, applicants had no knowledge that a GPA of 3.26 would play any role in the admissions process, a fact that was decided only after all applications had been submitted. The only GPA criterion publicized was that a GPA of 3.0 or higher was preferred, though applicants with lower GPAs could be admitted. It thus seems highly unlikely that there could be differential sorting across the 3.26 threshold. We confirm this in two ways.

First, as suggested by McCrary (2008), we show in figure A2 that the density of students just above the threshold looks similar to the density just below. Multiples of 0.1, as well as 3.0 and 4.0, are particularly common, but there is no clear difference in the distribution of GPAs around the eligibility threshold. Formal tests show no evidence that GPAs just above 3.26 are overrepresented relative to GPAs just below 3.26, suggesting no obvious manipulation by students. Second, we confirm that observable covariates are balanced across the threshold by running the specification in equation (1) using such covariates as outcomes. Table A3 shows the results of these covariate balance tests using a variety of bandwidths. There is no practically or statistically significant evidence of differential sorting across the threshold in terms of gender, race, citizenship, age, employment, or college major. The balance of density and covariates at the threshold suggests that students on either side of the threshold are similar along both observed and unobservable dimensions. Our regression discontinuity coefficients should therefore provide unbiased estimates of the impact of online access on educational trajectories.

## B. Causal Estimates

We first document how the GPA threshold affected the probability of admission to OMSCS. The relationship between GPA and the probability of being offered admission, seen in figure 3*A*, shows a clear discontinuity. The first-stage estimates in column 1 of table 5 suggest that those just above the GPA threshold were about 20 percentage points more likely to be admitted to the online program than their counterparts with slightly lower GPAs. This difference represents the extent to which the GPA threshold generated exogenous variation in access to the online option.

Importantly, access to the online program generates enrollment in that program. We define OMSCS enrollment as a student having enrolled in at least one semester by fall 2016.[22] At that point, all immediate and deferred admissions offers would have expired and applicants would have had the opportunity to apply to and enroll in other competing degree programs. Figure 3*B* shows the fraction of applicants who ever enrolled in OMSCS. The graphical evidence, as well as the estimates in column 2 of table 5, suggest that threshold-based admissibility increases enrollment in the online option by slightly more than 20 percentage points. This implies that roughly all of the marginal applicants admitted because of the GPA threshold accepted the offer of admission and enrolled. Instrumental variable estimates, shown in column 3, confirm that the matriculation rate of such students is close in magnitude and statistically indistinguishable from 100%. These applicants appear not to have competing options that would cause them to decline their admissions offer.

Importantly, though admission affects enrollment, admission timing appears not to. Figure A4 shows OMSCS enrollment rates as a function of GPA for the subsample of applicants offered admission. Those above the threshold were largely given immediate offers, and those below were largely given deferred offers, yet at the threshold there is no clear difference in the probability of enrolling in OMSCS, conditional on admission. The point estimate of the discontinuity is close to zero and statistically insignificant whether we use our default bandwidth of 0.5 or the Imbens-Kalyanaraman optimal bandwidth of 0.3.

Examination of enrollment in other programs confirms that OMSCS has no close substitutes. Figure 4*A* shows the fraction of OMSCS applicants who enrolled in other, non-OMSCS programs by fall 2016. We include any non-OMSCS degree program, regardless of field of study. The overall levels of such enrollment are quite low, with fewer than 20% just below the threshold enrolling elsewhere. The few alternatives chosen by such

[22] The relationship between spring 2014 enrollment and GPA in fig. A3 is consistent with the requirement of a GPA of at least 3.26 for immediate admission. Only four applicants below the GPA threshold appear to have enrolled in OMSCS in spring 2014.

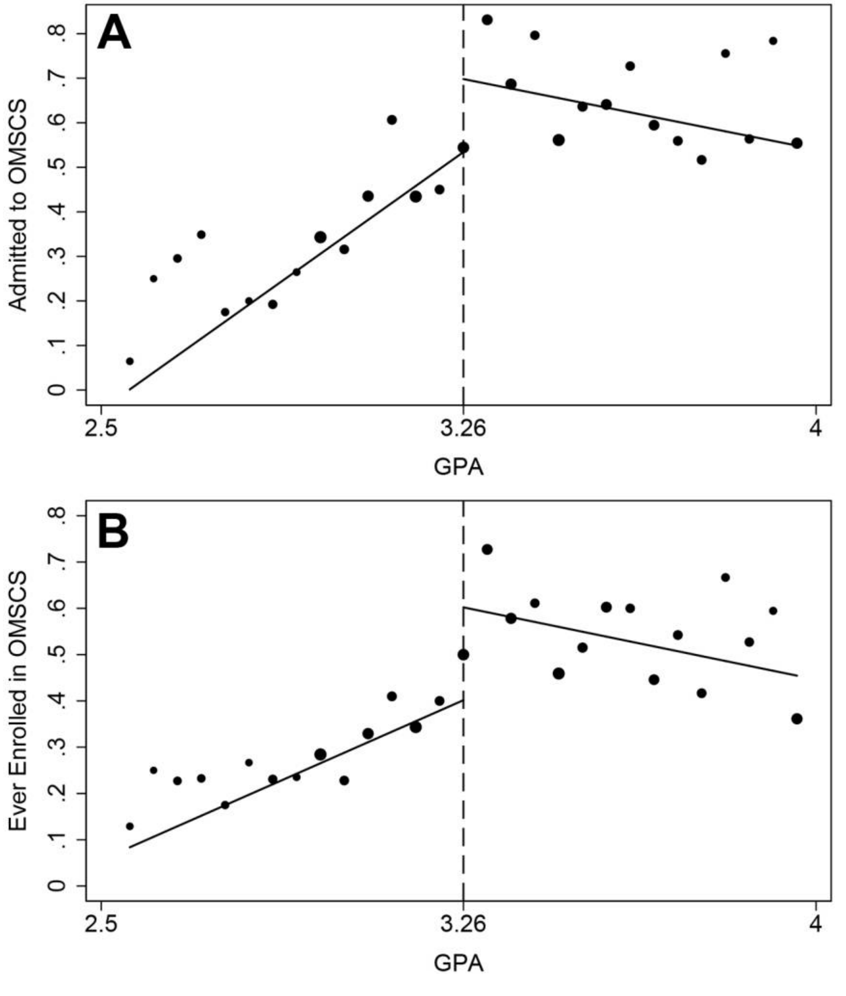


FIG. 3.—Access to and enrollment in the online program. *A*, Online admission. *B*, Online enrollment. The above figure shows as a function of college grade point average (GPA) the fraction of spring 2014 online program applicants who were admitted (*A*) and who enrolled (*B*) in the online program by fall 2016. The graph is limited to those with GPAs between 2.5 and 4.0. The dots shown come from binning the data in intervals of 0.05 from the threshold, with dot size proportional to the number of applicants in each bin. Also shown are fitted lines from a local linear regression discontinuity model using a bandwidth of 0.5, so that not all points shown are used to compute such predictions. OMSCS = Online Master of Science in Computer Science.

**Table 5**
**Access to Online Master of Science in Computer Science (OMSCS) and Enrollment in Higher Education**

| | Admitted | Enrolled OMSCS | | Enrolled Elsewhere | | Enrolled Anywhere | |
|---|---|---|---|---|---|---|---|
| | FS (1) | RF (2) | IV (3) | RF (4) | IV (5) | RF (6) | IV (7) |
| A. BW = .7: | | | | | | | |
| Admissible | .178*** | .194*** | 1.090*** | .007 | .038 | .177*** | .998*** |
| | (.062) | (.051) | (.214) | (.037) | (.213) | (.038) | (.305) |
| B. BW = .7, controls: | | | | | | | |
| Admissible | .189*** | .201*** | 1.063*** | .002 | .011 | .180*** | .951*** |
| | (.052) | (.040) | (.189) | (.034) | (.180) | (.036) | (.256) |
| C. BW = .5, controls: | | | | | | | |
| Admissible | .187*** | .212*** | 1.136*** | .046 | .245 | .223*** | 1.196*** |
| | (.066) | (.048) | (.257) | (.043) | (.283) | (.042) | (.402) |
| D. BW = .3, controls: | | | | | | | |
| Admissible | .218*** | .227*** | 1.043*** | .063 | .288 | .235*** | 1.079*** |
| | (.081) | (.068) | (.240) | (.054) | (.321) | (.053) | (.377) |
| Control mean | .41 | .36 | | .18 | | .51 | |

NOTE.—Heteroskedasticity-robust standard errors clustered by grade point average (GPA) are in parentheses. Each regression discontinuity estimate in cols. 1, 2, 4, and 6 comes from a local linear model that regresses an indicator for an admission or enrollment outcome on an indicator for being above the GPA threshold of 3.26, distance from that threshold, and the interaction of the two. Columns 3, 5, and 7 contain instrumental variable (IV) estimates of the impact of admission on enrollment, where admission has been instrumented with being above the threshold. The sample includes all spring 2014 applicants to OMSCS whose GPA is within the listed bandwidth (BW). The top row includes no controls, while the remaining rows control for gender, race/ethnicity, citizenship, age, employment, and college major. Enrollment is measured by fall 2016. The sample size in panels A and B is 1,706, in panel C is 1,365, and in panel D is 926. Listed below each column is the mean of the outcome for those 0.01–0.10 GPA points below the threshold. FS = first-stage regression; RF = reduced-form regression.
*** $p < .01$.

applicants are rarely the more prestigious competitors of MSCS, such as Carnegie Mellon or University of Southern California, but are instead lower-ranked online programs from institutions such as DeVry University or Arizona State University. This is in contrast to MSCS applicants, many hundreds of whom choose those prestigious competitors over Georgia Tech. Figure 4*B* shows that over 50% of MSCS applicants enroll in alternative US programs, a fraction that rises to 65% when considering just US applicants to the in-person program. Those interested in the online program appear to have fewer competing alternatives than those interested in the in-person program.

In addition to the low overall rate of online program applicants enrolling in alternatives to OMSCS, there is also no visually apparent discontinuity in non-OMSCS enrollment, with columns 4 and 5 of table 5 showing statistically insignificant point estimates close to zero. If access to OMSCS were substituting for other in-person programs, we would expect to see a clear drop in enrollment elsewhere to the right of the GPA threshold. Though our regression discontinuity estimates are generated by those at a particular

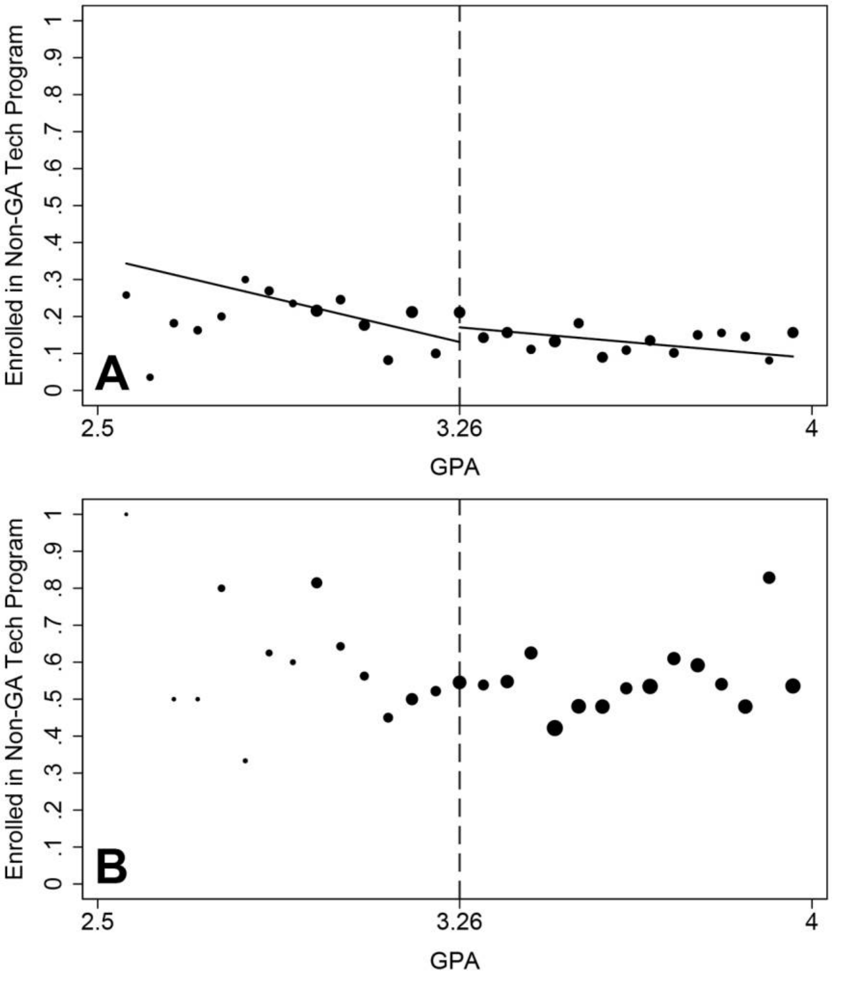


FIG. 4.—Enrollment in other programs. *A*, Online program applicants. *B*, In-person program applicants. The above figure shows as a function of college grade point average (GPA) the fraction of spring 2014 online program applicants (*A*) and fall 2013 and 2014 in-person program applicants (*B*) who by fall 2016 had enrolled in any formal non–Georgia Tech (GA Tech) program, regardless of field of study. The graph is limited to those with GPAs between 2.5 and 4.0. The dots shown come from binning the data in intervals of 0.05 from the threshold, with dot size proportional to the number of applicants in each bin. Also shown in *A* are fitted lines from a local linear regression discontinuity model using a bandwidth of 0.5, so that not all points shown are used to compute such predictions.

point in the GPA distribution, it is worth noting that those with much higher or lower GPAs also do not appear to enroll in non-OMSCS options. This suggests that the market is not providing appealing alternatives for a wide range of students for whom OMSCS is appealing. In contrast, most MSCS applicants with lower and higher GPAs find suitable alternatives in which to enroll.

Access to the online option therefore increases the number of people pursuing education at all. We see this in figure 5, which shows the fraction of applicants enrolling in any formal higher education. There is a large, clear discontinuity at the admissions threshold, with estimates from column 6 of table 5 suggesting that admissibility to the online program increases enrollment in formal higher education by about 20 percentage points. The instrumental variable estimates in column 7 imply that roughly 100% of the marginal admits to OMSCS represent new entrants into formal higher education. Access to this online option thus increases the number of people pursuing education.

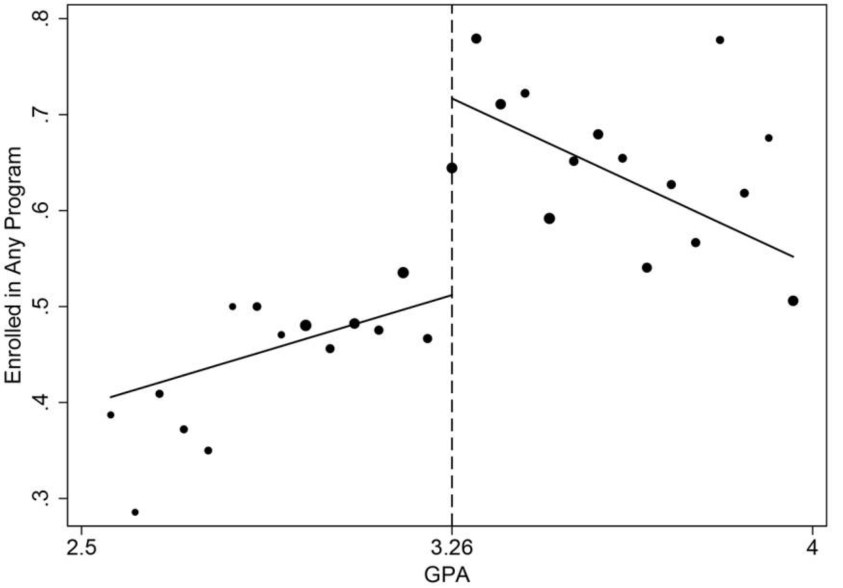


FIG. 5.—Enrollment in any degree program. The above figure shows as a function of college grade point average (GPA) the fraction of spring 2014 online program applicants who by fall 2016 had enrolled in any program, Online Master of Science in Computer Science or otherwise. The graph is limited to those with GPAs between 2.5 and 4.0. The dots shown come from binning the data in intervals of 0.05 from the threshold, with dot size proportional to the number of applicants in each bin. Also shown are fitted lines from a local linear regression discontinuity model using a bandwidth of 0.5, so that not all points shown are used to compute such predictions.

We perform a number of robustness checks to confirm that our estimates are not sensitive to our specification choices. The first two rows of table 5 show that inclusion of demographic controls improves the precision of our estimates but does not meaningfully alter their magnitude. The remaining rows of the table show that our point estimates are robust to a fairly wide set of bandwidths, including those close to the optimal bandwidths mentioned previously. To check that our estimated discontinuities in admission, OMSCS enrollment, and overall enrollment are not driven by spurious features of the data, we test for placebo discontinuities by running our baseline regression specification placing the admissions threshold at GPA values other than 3.26. The resulting coefficients are shown in figures A5*A*–A7*A*. In all cases, the actual threshold of 3.26 generates the largest discontinuity and is the only one that is positive and statistically significant.

One other potential concern is that the location of the threshold was endogenous to the quality of the applicant pool in that part of the GPA distribution. If students with a 3.26 GPA were of particularly high quality and thus ended the admissions process by using up the program's final capacity, then our estimates might be biased by correlations between such quality and enrollment decisions. To test whether such an endogenous threshold location is generating bias, figures A5*B*–A7*B* show estimated discontinuities from donut hole regression discontinuity specifications that exclude observations close to the threshold. The resulting coefficients are, if anything, slightly larger, suggesting that our estimates are not driven by observations very close to the threshold.

As a final check, we explore heterogeneity in enrollment impacts of online access in table 6. Limiting the sample to non-AT&T employees has little effect on our point estimates, suggesting that our results are not driven by this potentially unusual subset of applicants. Limiting the sample to US citizens has similarly little effect. Subsequent rows separate the sample by age, gender, and race. The main takeaway from these estimates is that there is no subgroup of applicants for whom access to OMSCS substitutes for enrollment in other formal degree programs. None of the point estimates in columns 4 and 5 is significantly negative. The result is that for all subgroups for whom the threshold clearly generates variation in access to OMSCS, such access clearly increases overall enrollment in higher education.

### C. Nondegree Training

Having shown that OMSCS does not substitute for enrollment in other graduate degree programs, we use the survey to explore how it affects informal training. The first column of table 7 shows the impact of passing the admissions threshold on the survey response rate.[23] Although both suggest

[23] Figure A1 plots the response rate by GPA.

**Table 6**
**Heterogeneity in Enrollment Impacts of Access to Online Option**

| | Admitted | Enrolled OMSCS | | Enrolled Elsewhere | | Enrolled Anywhere | |
|---|---|---|---|---|---|---|---|
| | FS (1) | RF (2) | IV (3) | RF (4) | IV (5) | RF (6) | IV (7) |
| Excluding AT&T | .225*** | .265*** | 1.178*** | .036 | .158 | .260*** | 1.154*** |
| | (.078) | (.058) | (.248) | (.052) | (.263) | (.051) | (.372) |
| *N* | 1,062 | 1,062 | 1,062 | 1,062 | 1,062 | 1,062 | 1,062 |
| US citizen | .157** | .217*** | 1.381*** | .009 | .055 | .204*** | 1.299** |
| | (.071) | (.054) | (.416) | (.049) | (.327) | (.050) | (.560) |
| *N* | 1,193 | 1,193 | 1,193 | 1,193 | 1,193 | 1,193 | 1,193 |
| Age ≥ 35 | .309*** | .300*** | .970*** | −.050 | −.161 | .221*** | .716*** |
| | (.070) | (.069) | (.125) | (.064) | (.200) | (.070) | (.200) |
| *N* | 668 | 668 | 668 | 668 | 668 | 668 | 668 |
| Age < 35 | .082 | .154** | 1.866 | .109** | 1.323 | .213*** | 2.580 |
| | (.088) | (.072) | (1.501) | (.051) | (1.807) | (.069) | (2.530) |
| *N* | 697 | 697 | 697 | 697 | 697 | 697 | 697 |
| Male | .161** | .216*** | 1.340*** | .010 | .065 | .195*** | 1.212** |
| | (.071) | (.051) | (.399) | (.053) | (.346) | (.051) | (.554) |
| *N* | 1,184 | 1,184 | 1,184 | 1,184 | 1,184 | 1,184 | 1,184 |
| Female | .362** | .206 | .570** | .197* | .545 | .347** | .959** |
| | (.140) | (.130) | (.252) | (.112) | (.416) | (.139) | (.386) |
| *N* | 181 | 181 | 181 | 181 | 181 | 181 | 181 |
| White or Asian | .218*** | .256*** | 1.172*** | .018 | .081 | .247*** | 1.130*** |
| | (.069) | (.053) | (.221) | (.048) | (.234) | (.048) | (.331) |
| *N* | 1,067 | 1,067 | 1,067 | 1,067 | 1,067 | 1,067 | 1,067 |
| Black or Hispanic | .040 | .000 | .007 | .202** | 4.998 | .068 | 1.695 |
| | (.114) | (.115) | (2.845) | (.100) | (14.541) | (.123) | (4.429) |
| *N* | 243 | 243 | 243 | 243 | 243 | 243 | 243 |

NOTE.—Heteroskedasticity-robust standard errors clustered by grade point average (GPA) are in parentheses. Each regression discontinuity estimate in cols. 1–4 comes from a local linear model that regresses an indicator for an admission or enrollment outcome on an indicator for being above the GPA threshold of 3.26, distance from that threshold, and the interaction of the two. Columns 5 and 6 contain instrumental variable (IV) estimates of the impact of admission on enrollment, where admission has been instrumented with being above the threshold. The sample includes all spring 2014 applicants to Online Master of Science in Computer Science (OMSCS) whose GPA is within 0.5 of the admissions threshold and who belong to the listed subgroup. All regressions control for the gender, race, geography, age, employment, and college major variables listed in table 1. Enrollment is measured by fall 2016.
* $p < .10$.
** $p < .05$.
*** $p < .01$.

that students with GPAs above the admissions threshold have higher response rates, these differences are small and insignificant, suggesting that selection into the survey sample is unlikely to generate substantial bias.

Table 7 utilizes the regression discontinuity design to determine the impact of access to OMSCS on informal training. There is no evidence that access to OMSCS reduces hours spent on nondegree training. Our point estimates, while small and insignificant, suggest that access to OMSCS actually increases informal education, with some specifications showing that OMSCS

**Table 7**
**Access to Online Master of Science in Computer Science (OMSCS) and Nondegree Training**

| | | Hours Spent on Nondegree Training | | | | | Hours Spent on | |
|---|---|---|---|---|---|---|---|---|
| | Responded to Survey (1) | Any Type (2) | MOOC (3) | Professional Certification (4) | Boot Camp (5) | Other Type (6) | Degree Training (7) | All Training (8) |
| A. BW = .7: | | | | | | | | |
| Admissible (RF) | .022 | 13.810 | −4.816 | 9.195 | 15.131* | −5.701 | 293.456** | 307.266** |
| | (.053) | (27.790) | (18.027) | (10.048) | (7.832) | (11.765) | (124.258) | (124.258) |
| Admitted (IV) | .125 | 89.007 | −31.041 | 59.266 | 97.524 | −36.742 | 1,891.409** | 1,980.416** |
| | (.289) | (190.079) | (118.099) | (74.870) | (71.952) | (73.584) | (807.888) | (862.136) |
| *N* | 1,706 | 649 | 649 | 649 | 649 | 649 | 649 | 649 |
| B. BW = .7, controls: | | | | | | | | |
| Admissible (RF) | .032 | 7.057 | −8.230 | 7.842 | 15.080* | −7.636 | 285.524** | 292.581** |
| | (.053) | (28.169) | (18.459) | (9.844) | (7.660) | (12.555) | (121.105) | (123.066) |
| Admitted (IV) | .170 | 45.913 | −53.543 | 51.021 | 98.113 | −49.678 | 1,857.621** | 1,903.534** |
| | (.278) | (185.739) | (123.844) | (69.355) | (66.988) | (80.885) | (721.949) | (759.458) |
| *N* | 1,706 | 649 | 649 | 649 | 649 | 649 | 649 | 649 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| C. BW = .5, controls: | | | | | | | | |
| Admissible (RF) | .048 | 18.604 | −3.135 | 19.679 | 11.028 | −8.969 | 294.394** | 312.998** |
| | (.062) | (30.779) | (21.518) | (11.141) | (7.766) | (13.803) | (147.483) | (151.729) |
| Admitted (IV) | .256 | 97.548 | −16.436 | 103.185 | 57.827 | −47.027 | 1,543.630** | 1,641.178** |
| | (.325) | (168.093) | (114.243) | (77.112) | (50.738) | (71.786) | (631.961) | (677.440) |
| *N* | 1,365 | 512 | 512 | 512 | 512 | 512 | 512 | 512 |
| D. BW = .3, controls: | | | | | | | | |
| Admissible (RF) | .048 | 37.644 | −1.620 | 29.172 | 11.471 | −1.380 | 349.310* | 386.954* |
| | (.087) | (34.869) | (25.604) | (18.014) | (10.762) | (14.749) | (189.433) | (197.774) |
| Admitted (IV) | .222 | 153.477 | −6.603 | 118.937 | 46.769 | −5.626 | 1,424.155** | 1,577.632** |
| | (.394) | (160.518) | (104.836) | (96.131) | (50.495) | (59.917) | (623.471) | (690.736) |
| *N* | 926 | 346 | 346 | 346 | 346 | 346 | 346 | 346 |
| Control mean | .37 | 89.00 | 44.88 | 7.85 | 1.08 | 35.19 | 670.50 | 759.50 |

NOTE.—Heteroskedasticity-robust standard errors clustered by grade point average (GPA) are in parentheses. The regression discontinuity estimate in the top row of each panel comes from a local linear model that regresses the listed outcome on an indicator for being above the GPA threshold of 3.26, distance from that threshold, and the interaction of the two. The bottom row of each panel contains instrumental variable (IV) estimates of the impact of admission on the listed outcome, where admission has been instrumented with being above the threshold. The sample includes all spring 2014 applicants to OMSCS whose GPA is within the listed bandwidth (BW) and who had valid survey responses. Outcomes refer to total hours spent on training from January 2014 through July 2017. The top panel includes no controls, while the remaining rows control for gender, race/ethnicity, citizenship, age, employment, and college major. Listed below each column is the mean of the outcome for those 0.01–0.10 GPA points below the threshold. MOOC = massive online open course; RF = reduced-form regression.

* $p < .10$.

** $p < .05$.

admissibility causes marginally significant increases in time spent on professional certification programs and coding boot camps. Figure 6 graphically depicts our results for all types of nondegree training combined, while figure A8 shows the results for different types of training separately.

Column 7 of table 7 unsurprisingly shows that admission to OMSCS substantially increases the number of hours spent on degree-based training. These estimates use the assumption that students spend 18 hours per week on classwork each semester for which they are enrolled in a degree program (Georgia Tech's estimate for the workload in OMSCS). Under this assumption, we find that admission to OMSCS increases degree training by 1,400–1,900 hours over the 3.5-year period in question. Because the number of hours spent on nondegree training is so small relative to degree training, estimated impacts of OMSCS admission on total training hours are similar to those spent on degree training. Figure 7 graphically shows the jump in total hours of training at the admission threshold, while table A4 explores the robustness of these results to different assumptions about the hours spent in different types of de-

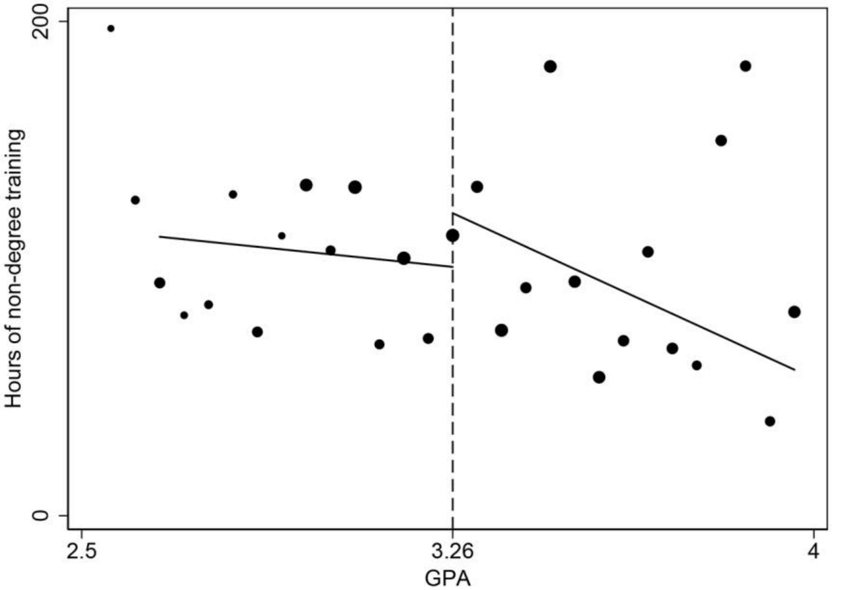


Fig. 6.—Hours of nondegree training. The above figure shows as a function of college grade point average (GPA) the total number of hours respondents to the July 2017 survey report having spent in nondegree training since January 2014. The graph is limited to those with GPAs between 2.5 and 4.0. The dots shown come from binning the data in intervals of 0.05 from the threshold, with dot size proportional to the number of applicants in each bin. Also shown are fitted lines from a local linear regression discontinuity model using a bandwidth of 0.5, so that not all points shown are used to compute such predictions.

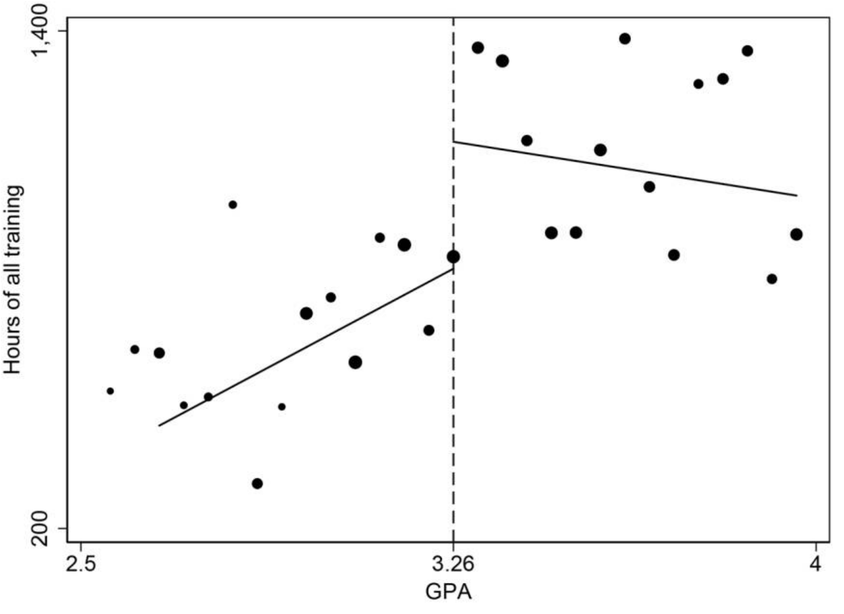


FIG. 7.—Total hours of training. The above figure shows as a function of college grade point average (GPA) the total number of hours respondents to the July 2017 survey spent on all training since January 2014. Degree training hours come from assuming a commitment of 18 hours per week for 13 weeks during each semester enrolled according to the National Student Clearinghouse data. All training hours add to that the nondegree training hours reported by respondents. The graph is limited to those with GPAs between 2.5 and 4.0. The dots shown come from binning the data in intervals of 0.05 from the threshold, with dot size proportional to the number of applicants in each bin. Also shown are fitted lines from a local linear regression discontinuity model using a bandwidth of 0.5, so that not all points shown are used to compute such predictions.

gree training. Regardless of the assumption we make, we find that access to OMSCS has a large and significant impact on total training.

## V. Discussion and Conclusion

Our descriptive evidence shows large demand for the first low-cost online degree offered by a highly ranked institution. Applicant pools to the online and in-person versions of this degree program show almost no overlap in individuals or demographic characteristics. Unlike its in-person equivalent, the online option generates demand largely from midcareer Americans. Large demand from older, employed individuals is consistent with the idea that the geographic and temporal flexibility of the online option are critical to its appeal. Online education can provide midcareer training without forcing individuals to quit their jobs or move to locations with appropriate educational institutions. Relatively low demand for the online option from non-Americans is consistent with the value of in-person programs, stemming at least partially from physical access to US social networks and labor markets.

Our causal evidence shows that this online option expands access to education and does not substitute for other informal training. Eighty percent of those accepted by OMSCS enroll. The vast majority of applicants denied access do not pursue any further form of formal education. Most importantly, gaining access to the online option does not decrease the extent to which students enroll in other educational programs or nondegree training. This is the first rigorous evidence that we know of showing that an online degree program can increase educational attainment, implying that the higher education market had previously been failing to meet demand for this particular bundle of program characteristics.

This model of online education thus has the potential to substantially increase the national stock of computer science human capital. OMSCS enrolls about 1,170 Americans annually. Though it is too early to measure completion rates, NSC data on the 2014 OMSCS enrollees suggest that at least 62% are still enrolled at least 2 years after they begin the program and thus are apparently on track to graduate. The actual fraction that will graduate may be substantially higher than that, given that the flexible nature of the program and midcareer students' busy professional and family lives make persistence somewhat difficult to measure. For example, over 25% of students who take a fall or spring semester off appear to reenroll in the subsequent spring or fall semester. Persistence to graduation could therefore be as high as 90%.[24] Conservatively, if only 62% of enrollees graduate, OMSCS will annually produce about 725 American computer science master's degree recipients. According to IPEDS's Completion Survey, about 11,000 American citizens earned a master's degree in computer science in 2013, the most recent year that data are available. This implies that OMSCS will generate a 7% increase in the national production of such degrees. If 90% of enrollees graduate, OMSCS will increase such production by 10%. Either way, the program will produce a substantial fraction of such computer science human capital.

We conclude with two questions raised by this research. The first concerns external validity. To what extent will the conclusions drawn from this particular online program apply to other populations and subjects? It seems likely, for example, that midcareer training in other fields might be amenable to this model. For example, UIUC's modeling of two degrees on OMSCS (an MBA and a data science master's) and the recent rise of micro-master's programs suggests that other institutions believe there are untapped markets in such training. Whether such low-cost, high-quality models can make inroads in undergraduate or secondary education remains to be seen.

[24] By comparison, about 95% of MSCS students graduate within 2 years.

The second question concerns the quality of the education that this online option provides. How large are the learning and labor market impacts of this online degree, and how do they compare to that of the in-person equivalent? Comparing the undergraduate colleges attended by OMSCS and MSCS students suggests that OMSCS students are on average somewhat weaker academically than their in-person counterparts. Nonetheless, comparisons of student achievement across the online and in-person formats suggest that OMSCS students finish their courses with at least as much knowledge as their in-person counterparts (Goel and Joyner 2016). We hope to explore in subsequent work the extent to which the OMSCS degree is valued by the labor market and whether and how it affects career advancement. Whether the labor market perceives OMSCS graduates as similar in quality to their in-person counterparts will have implications for the impact of such models on the postsecondary sector more generally (Hoxby 2014).

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