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Does Online Delivery Increase Access to Education?

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Abstract

Though online technology has generated excitement about its potential to increase access to education, most research has focused on comparing student performance across online and in-person formats. We provide the first evidence that online education affects the number of people pursuing formal education. We study Georgia Tech's Online M.S. in Computer Science, the earliest model to combine the inexpensive nature of online education with a highly regarded degree program. Regression discontinuity estimates exploiting an admissions threshold unknown to applicants show that access to this online option substantially increases overall enrollment in formal education, expanding the pool of students rather than substituting for existing educational options. Demand for the online option is driven by mid-career Americans. By satisfying large, previously unmet demand for mid-career training, this single program will boost annual production of American computer science master's degrees by about eight percent. More generally, these results suggest that low cost, high quality online options may open opportunities for populations who would not otherwise pursue education.

1 Introduction

Online coursework has been heralded as potentially transformative for higher education, possibly lowering costs of delivery and increasing access for disadvantaged students. From 2002 through 2012, the number of online bachelor's degrees awarded rose from 4,000 to 75,000, or five percent of all U.S. bachelor's degrees issued that year (Deming et al., 2015). The federal government estimates that 27 percent of college students were taking at least one course online as of 2013, the most recent year for which data exists.[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 does 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 et al., 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., 2015). 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 et al., 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 formal education. This is in part because the ubiquity of such options makes it difficult to construct convincing counterfactuals. Understanding the impact of online education depends, however, on whether online classes replace in-person classes or generate additional human capital investment.

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

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 ten in the United States, started 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 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 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 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 degree program 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 to 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 35-year old mid-career American. Over three-fourths of those admitted to the online program accept those offers and enroll, suggesting few find alternative compelling educational options. Large demand from a mid-career population uninterested in its in-person equivalent and a high matriculation rate both suggest the online program is drawing in students who would not otherwise enroll elsewhere.

Next, we rigorously estimate whether this online option expands access to students who would not otherwise enroll and thus increases the numbers of students participating in higher education. To do so, we utilize quasi-random variation in admission to OMSCS to determine whether gaining access to OMSCS reduces the extent to which students enroll in other programs. We exploit the fact that capacity constraints for the earliest applicant cohort resulted in the existence of a GPA threshold of 3.26 for admission to the program, a threshold that was arbitrary and unknown to applicants. With National Student Clearinghouse data that tracks enrollment in any U.S. formal higher education, we use a regression discontinuity design to compare enrollment outcomes for applicants just above and below that threshold, two groups who differ only in their access to this online option.

We find that the threshold generates a roughly 20 percentage point difference in the probability of admission to and enrollment in the online program, suggesting that roughly all of the marginal admits matriculate. We show that very few applicants to OMSCS ultimately enroll in other, non-OMSCS programs. Those just below the 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. Given the size of the program's enrollment and early evidence on persistence, our estimates suggest that this program will boost annual production of American computer science master's degrees by about eight percent.

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, low ranked institutions offering inexpensive degrees with low labor market returns (Deming et al., 2016), or free massive online open courses (MOOCs) with unclear returns and very high attrition rates (Perna et al., 2013; Banerjee and Duflo, 2014). Because OMSCS' price-quality pairing had not been previously seen in online education, the New York Times declared that this model meant "disruption may be approaching."[2] 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.[3]

The low-cost, high quality model pursued by OMSCS appears 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 MBA. The degree costs about $22,000, roughly one-third the cost of the in-person MBA offered by UIUC and similarly ranked institutions. 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 MIT announced plans to offer micro-master'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 fourth 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, and social work from the University of Michigan at Ann Arbor.[4] That more highly ranked institutions appear to be entering the market for inexpensive online degrees suggests our results may be increasingly relevant to the future of online education.

The remainder of the paper proceeds as follows. In section 2, we describe the OMSCS program in more detail, describe the available data, and descriptively compare the applicant pools to the in-person and online programs. In section 3, we present regression discontinuity estimates of the impact of online access on overall enrollment. In section 4, 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 eight percent. We also discuss the

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[2] T. Lewin (2013), "Master's Degree Is New Frontier of Study Online" New York Times, August 17.

[3] B. Obama (2015), "Remarks by the President Announcing Student Aid Bill of Rights." March 10 https://www.whitehouse.gov/the-press-office/2015/03/10/remarks-president-announcing-student-aid-bill-rights.

[4] J. Young (2016), "Online 'Micro-Master's' Programs Extend Their Reach" Chronicle of Higher Education, September 20.

external validity of these findings, as well as concerns about the quality of education delivered by the online program.

2 Context and Data

2.1 The OMSCS Degree Program

Georgia Tech's Computer Science Department had two partners in creating OMSCS. The first was Udacity, one of the largest providers of massive open online courses. OMSCS courses are offered through a platform designed by Udacity. 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 to seven semesters, which can include summer terms. In order 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 in-person degree, OMSCS is accredited as the accreditor considers it equivalent to the in-person program.

Though deadlines for submitting assignments are the same as 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 fora 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]

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[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

The second partner, AT&T, provided roughly $4,000,000 in startup funding. Much of that funded production of the roughly 30 courses OMSCS offers, each of which initially cost 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 re-broadcast in-person lectures, as some online courses do but instead produces original videos and other materials 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 as "preferred qualifications" having a B.A. in computer science or related field with an undergraduate GPA of 3.0 or higher.[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." Conversely, the admissions website to MSCS describes a GPA of 3.0 as a "desirable minimum" and notes that "most candidates score higher." MSCS also requires submission of GRE scores, which OMSCS does not. Whereas MSCS has one cohort of applicants each year who apply to start in the fall, OMSCS has two application 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. We turn now to a description of our data and the applicants to both programs.

2.2 Data

We have data from Georgia Tech's Computer Science Department on all applicants to OMSCS's first three cohorts, for whom classes started in spring 2014, fall 2014, and spring 2015. We also have data on two cohorts of applicants to MSCS, those applying to start classes in fall 2013 and fall 2014. For each applicant, we have basic self-reported demographic information including age,

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from IBM's Watson platform. Jill regularly answered students' questions and was only revealed to them as virtual late in the semester.

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

gender, race/ethnicity and citizenship. Applicants also report post-secondary educational history, including the name of each college attended, the applicant's 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 National Student Clearinghouse (NSC), an organization that tracks enrollment at post-secondary 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 percent and generally above 90 percent in other states (Dynarski et al., 2015). Importantly, we do observe many for-profit and nonprofit institutions that primarily offer online coursework, such as University of Phoenix and Western Governor's University. We supplement this with data from the National Science Foundation on the full population of students earning computer science master's degrees in the United States in 2013, the most recent year available.

3 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 3,600 applicants annually, more than twice as many as its in-person equivalent. It admits 55 percent of those applicants, more than triple the 15 percent admission rate for the in-person program.

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[7] Though the NSC also records degree completion, it is too early to measure this given that most initial OMSCS enrollees have not yet been enrolled for the two to three years expected for graduation.

OMSCS is thus less selective and more open than its in-person counterpart, as program designers intended. Three-fourths of those admitted to the online program enroll, so that each year roughly 1,500 students begin a computer science master's degree through OMSCS, more than 10 times as many who begin a degree through MSCS. This makes OMSCS the largest computer science master's degree program in the United States. By way of comparison, the NSF estimates that U.S. 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 seven percent of all computer science master's degrees in the country. The roughly 1,150 annual American enrollees in OMSCS would represent over ten percent 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, only 20 of the 8,500 applicants to either program in our data applied to both programs, suggesting that students view these programs as distinct educational products. Second, as panel B in Table 1 shows, the applicant pools to the two programs look very different, particularly in terms of nationality and age.[8]

The online program attracts a much more American demographic than does the in-person program. Three-fourths of the online applicants are U.S. citizens, compared to less than one-tenth 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 percent) or China (nearly 20 percent). After admissions and enrollment decisions, the fraction of in-person enrollees who are U.S. citizens rises to 26 percent. Even so, over half of that student body are Indian or Chinese citizens. Panel B shows that only 10 percent of applicants to the online program are Indian or Chinese citizens, proportions that do not change substantially with admissions and enrollment decisions. That international applicants show stronger demand for the in-person program suggests such students may value the opportunity to be physically present in the U.S., which admission to an online program does not grant.[9] That 75 percent of online program enrollees are U.S. citizens makes that

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[8] Table A.1 shows the characteristics of individual cohorts of applicants. None of the demographic facts highlighted here change meaningfully over the observed time period.

[9] Low international awareness of OMSCS' existence seems unlikely to explain this fact, as Table A.1 shows that the international composition of the applicant pool has not changed substantially as time has passed and such awareness has likely increased.

pool substantially more American than the national pool of those completing computer science master's degrees, of whom 52 percent are U.S. citizens.

The online program attracts a substantially older demographic than does the in-person program. Online applicants are on average 35 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 percent of in-person applicants are 25 years old or younger and over 95 percent are 30 or younger. Nearly no one older than 30 applies to the in-person program. The opposite is true of the online program. Fewer than 10 percent of online applicants are 25 or younger and only 25 percent are between 25 and 30. The remaining two-thirds of applicants are over 30 years old, with substantial representation of those in their 40s and 50s.

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. Ninety percent of online applicants list a current employer, relative to 50 percent of in-person applicants.[10] Table 2 shows more detail about the employment of online applicants, 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.[11] Well-represented in the list are technology giants (Microsoft, Google, Amazon, Apple, IBM, Oracle, Cisco, Hewlett-Packard, Dell, Intel), military branches (Air Force, Army, Navy), defense contractors (Lockheed Martin, Raytheon, Northrop Grumman, Boeing), and consulting firms (Booz Allen Hamilton, Accenture). Apart from AT&T, firms with 12 or more employees applying to OMSCS comprise only 11 percent of the applicant pool. Firms with 2-11 applicants comprise another 16 percent of the applicant pool. Remarkably, nearly half of applicants to OMSCS appear to be the only employee from their firm applying to the program, suggesting that demand for such training is widespread and not simply concentrated among a few large firms.

The online and in-person applicant and enrollee pools look fairly similar in terms of gender

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[10] Employment information is missing for the 2013 MSCS applicants, so the 50 percent figure is based on 2014 MSCS applicants. Those two waves look similar along other dimensions so that employment figure is unlikely to be very different in the 2013 pool.

[11] As seen in Table A.1, the fact that 14 percent of OMSCS applicants are AT&T employees is driven largely by the first cohort of applicants, of whom 23 percent were from AT&T. That proportion drops to fewer than 10 percent in subsequent cohorts.

and race, particularly when the sample is limited to U.S. citizens. Only 13 percent of U.S. citizen online applicants are female, a proportion quite similar to the in-person program.[12] Among U.S. citizens, the online applicant pool is 64 percent white, 18 percent black or Hispanic, and 14 percent Asian, proportions roughly similar to the in-person 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 applicants pools.[13]

We can, however, use as proxies for family background and academic skill the characteristics of applicants' undergraduate institutions. To do so, we use data from the Integrated Postsecondary Education Data System (IPEDS) to characterize all applicants who attended U.S. colleges by the characteristics of those colleges.[14] Table 3 shows clear differences across the two applicant pools. Relative to in-person applicants, online applicants come from colleges with a higher proportion of low income students (measured by Pell grant receipt), lower graduation rates, and lower SAT scores.[15] 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.

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 formal higher education market. First, though the two programs culminate in the same degree, there is nearly no overlap in the pop-

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[12] 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 than American applicants to be female.

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

[14] 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 66 percent of OMSCS applicants and 12 percent of MSCS applicants to colleges in IPEDS.

[15] The difference in math SAT scores shown for applicants represents 0.17 student-level standard deviations.

ulations 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 35-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, over three-fourths of those admitted to the online program accept those offers and enroll, suggesting that relatively few such admits find alternative higher education options compelling. Large demand for OMSCS from a mid-career population uninterested in its in-person equivalent and the high enrollment rate among admits both suggest that OMSCS provides an educational option for which there has previously been no compelling, competing option. 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.

4 The Impact of Online Access on Educational Trajectories

4.1 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 and differ along other dimensions when compared to those denied admission. Comparison of 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 order of undergraduate GPA (from highest to lowest) and offered immediate admission only to the first 500 or so applications he read 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.

Slightly complicating this process is the fact that all applications were ultimately read 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 can not distinguish between students made offers of admission for spring 2014 and those who were offered deferred admission. To deal with this complication, we measure enrollment outcomes as of spring 2015, at which point 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.

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 (RD) that compares the educational trajectories of applicants just above and 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 through the following baseline specification:

$$Enrolled_i = \beta_0 + \beta_1 Admissible_i + \beta_2 GPA_i + \beta_3 Admissible_i \times GPA_i + \epsilon_i. \tag{1}$$

Here, $Enrolled$ indicates enrollment status in OMSCS or other programs for spring 2014 applicant i, $Admissible$ indicates the applicant is above the GPA threshold and GPA measures his 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 variables 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

$$Admitted_i = \alpha_0 + \alpha_1 Admissible_i + \alpha_2 GPA_i + \alpha_3 Admissible_i \times GPA_i + \epsilon_i. \tag{2}$$

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

$$Enrolled_i = \gamma_0 + \gamma_1 Admitted_i + \gamma_2 GPA_i + \gamma_3 Admissible_i \times GPA_i + \epsilon_i. \tag{3}$$

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. We use as our default bandwidth 0.50 GPA points, which corresponds closely to the Imbens-Kalyanaraman optimal bandwidth for most outcomes (Imbens and Kalyanaraman, 2012). To improve precision, we include demographic controls for gender, race/ethnicity, citizenship, age, employment and college major. We show that our results are robust to use of different bandwidths and exclusion of demographic controls.

Validity of our RD 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 may 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 A.1 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 over-represented 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 A.2 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 suggest 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.

4.2 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 Panel A of Figure 3, shows a clear discontinuity. The first stage estimates in column 1 of Table 4 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. The relationship between spring 2014 enrollment and GPA in Figure A.2 is consistent with the requirement of a GPA of at least 3.26 for immediate admission.[16] To generate an enrollment measure consistent with our admissions measure, which combines both immediate and deferred admissions offers, we define OMSCS enrollment as a student having enrolled in at least one semester by spring 2015.

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[16] Only four applicants below the GPA threshold appear to have enrolled in OMSCS in spring 2014.

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.

Panel B of Figure 3 shows the fraction of applicants who ever enrolled in OMSCS. The graphical evidence, as well as the estimates in column 2 of Table 4, 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 variables estimates, shown in column 3, confirm that the matriculation rate of such students is roughly 100 percent.[17] These applicants appear not to have competing options that would cause them to decline their admissions offer.

Examination of enrollment in other programs confirms that OMSCS has no close substitutes. Panel A of Figure 4 shows the fraction of OMSCS applicants who enrolled in other, non-OMSCS programs by spring 2015. The overall levels of such enrollment are quite low, with 11 percent of those just below the threshold enrolling elsewhere. The few alternatives chosen by such 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.

There is no visually apparent discontinuity in non-OMSCS enrollment, with columns 4 and 5 of Table 4 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 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, suggesting the market is not providing appealing alternatives for a wide range of students.

Access to the online option therefore increases the number of people pursuing education at

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[17] Though admission affects enrollment, timing of that offer does not appear to. To show this, we show in Figure A.3 OMSCS enrollment rates as a function of GPA for those who were admitted. Those above the threshold were largely given immediate offers and those below deferred offers, yet no discontinuity is apparent. The point estimate of the discontinuity generated by using the Imbens-Kalyanaraman optimal bandwith is close to zero and statistically insignificant.

all. We see this in panel B of Figure 4, 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 4 suggesting that admissibility to the online program increases enrollment in formal higher education by over 20 percentage points. The instrumental variables estimates in column 7 imply that roughly 100 percent of the marginal admits to OMSCS represent new entrants into formal higher education. Access to this online option thus increases the number of people purusing education.

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 4 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 Imbens-Kalyanaraman optimal bandwidths. 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 panel A of Figures A.4, A.5 and A.6. In all cases, the actual threshold of 3.26 generates the largest discontinuity and 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 endogenous threshold location is generating bias, panel B of Figures A.4, A.5 and A.6 show estimated discontinuities from donut hole RD 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 5. 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 U.S. 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 educational programs. None of the point estimates in columns 4 and 5 are 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.

5 Discussion and Conclusion

Our descriptive evidence shows large demand for the first low cost online degree offered by a highly regarded institution. Applicant pools to the online and in-person versions of this degree program show almost no overlap in individuals or in demographic characteristics. Unlike its in-person equivalent, the online option generates demand largely from mid-career Americans. Large demand from older, employed individuals is consistent with the possibility that the geographic and temporal flexibility of the online option are critical to its appeal. Online education can provide mid-career 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 U.S. social networks and labor markets.

Our causal evidence shows that this online option expands access to formal education and does not substitute for other programs. Three-quarters of those accepted by OMSCS enroll. The vast majority of applicants denied access do not pursue any form of further formal education. Most importantly, gaining access to the online option does not decrease the extent to which students enroll in other educational programs. This is the first rigorous evidence that we know of showing 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 1,150 Americans annually, or

11 percent of the number of Americans earning computer science master's degrees each year.[18] Though it is too early to measure completion rates, 80 percent of OMSCS enrollees persist through at least the third semester, with nearly all withdrawals happening after the first semester and very few after the second.[19] If such persistence rates correspond to completion rates, OMSCS will annually produce approximately 900 American computer science master's degree recipients. Our best estimates suggest that this single program will thus generate an eight percent increase in the national production of such degrees.

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? Strong evidence of unmet demand for mid-career training in computer science does not necessarily mean that an undergraduate online computer science degree would generate similar demand. OMSCS is working with somewhat older students with a record of undergraduate success and existing evidence suggests that such academically strong students are precisely the ones whose learning suffers less from the online format. The large demand documented here also does not imply that high quality online graduate degrees in fields other than computer science would be appealing. Other subjects may not, for example, be as amenable to online study as computer science is.

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? Our evidence from colleges attended suggests that OMSCS students are, on average, somewhat weaker academically their in-person counterparts. Can Georgia Tech's computer science master's degree maintain its reputation while expanding the pool of degree holders? Interestingly, early comparisons of student achievement across the online and in-person formats suggests that OMSCS students finish their courses with at least as much knowledge as their in-person counterparts (Goel and Joyner, 2016).[20] We hope to explore in sub-

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[18] According to IPEDS' Completion Survey, accessed through the NSF's WebCaspar site, about 11,000 American citizens earned a master's degree in computer science in 2013.

[19] By comparison, 96 percent of MSCS students persist through the third semester.

[20] Assignments and exams were graded blindly across the same course in both programs, with graders unaware of whether the student had taken the in-person or online version of the course.

sequent 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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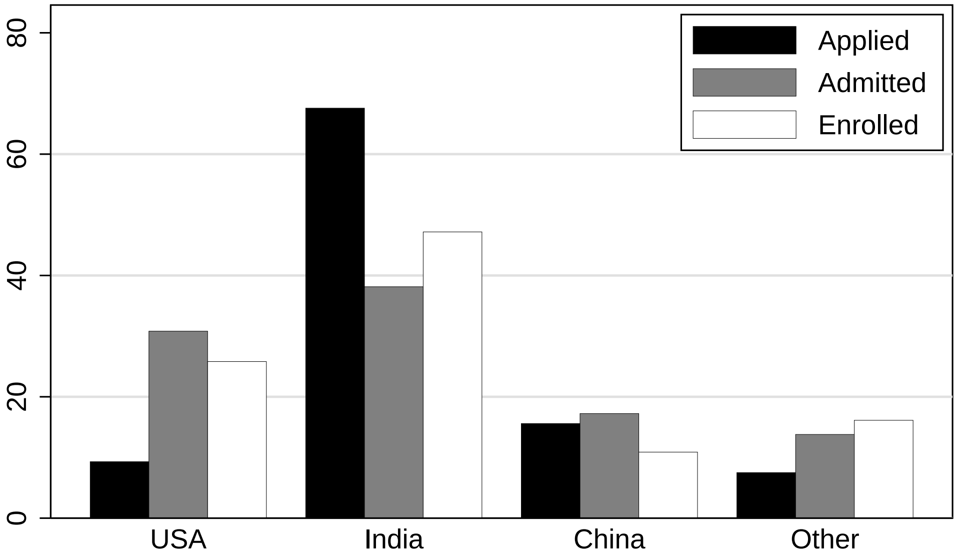
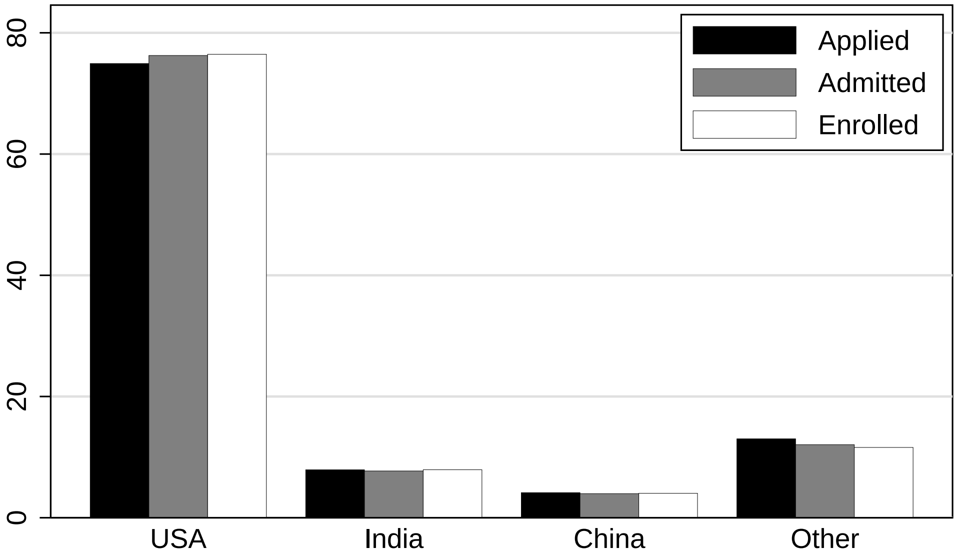
Figure 1: Nationality of MSCS and OMSCS Applicants

(A) MSCS Applicants

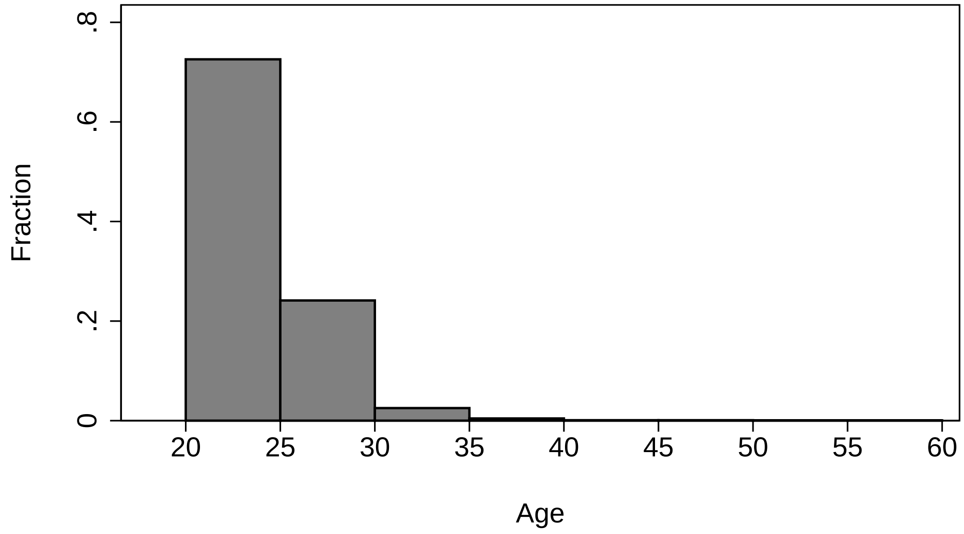


(B) OMSCS Applicants

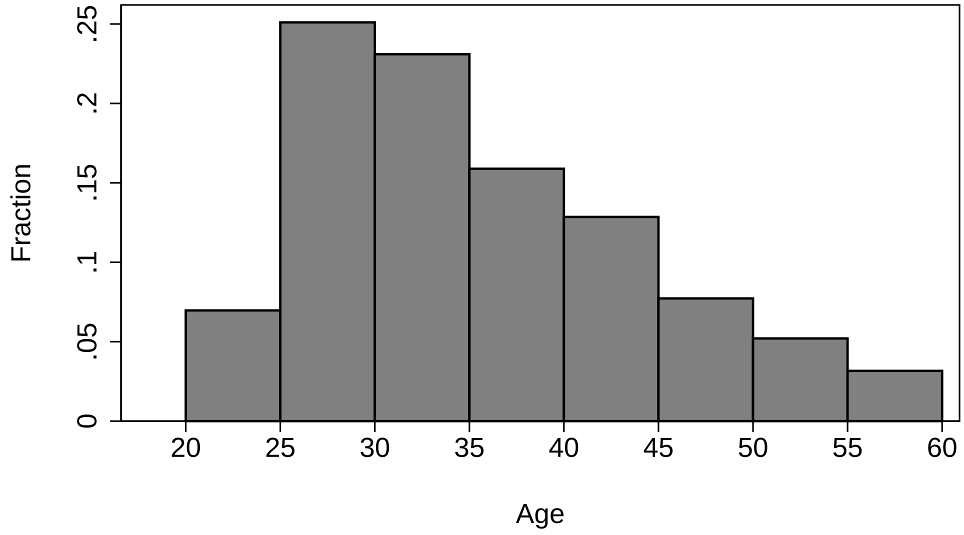


Notes: Panels A and B show the distribution of nationality of applicants to the MSCS and OMSCS programs respectively, where nationality is defined by self-reported citizenship. Panel A includes all 2013 and 2014 MSCS applicants. Panel B includes all spring 2014, fall 2014 and spring 2015 OMSCS applicants. From left to right, the three bars show the fraction of applicants, admitted students and enrolled students from a given country.

Figure 2: Age Distribution of MSCS and OMSCS Applicants



(A) MSCS Applicants

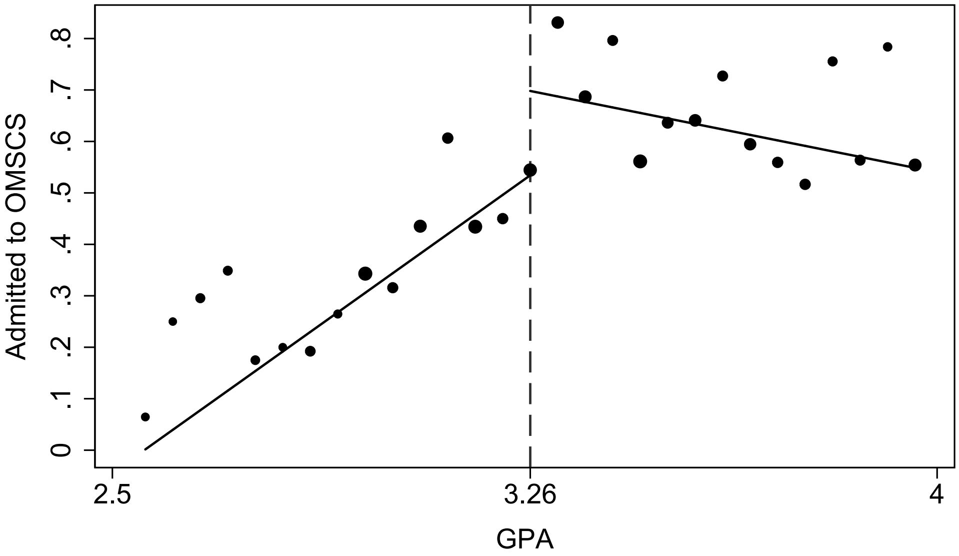


(B) OMSCS Applicants

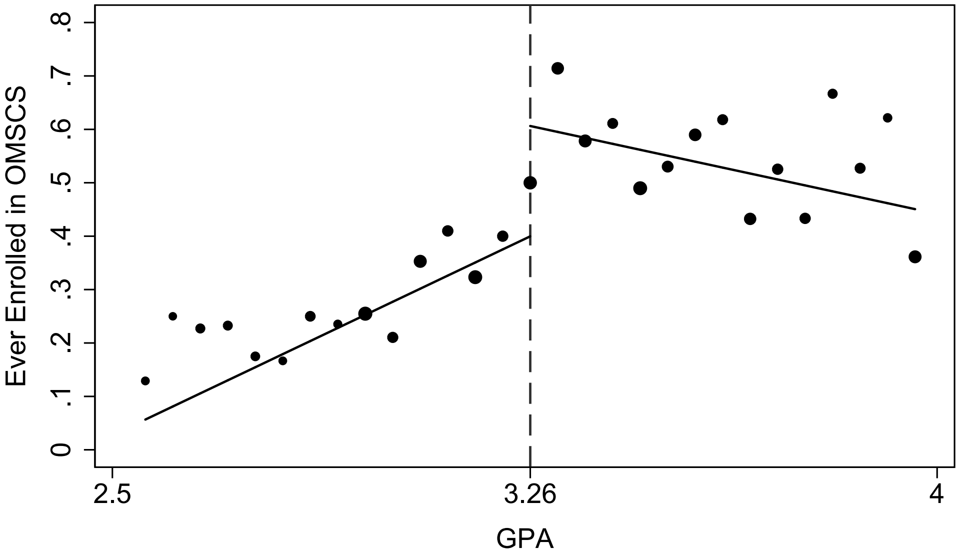
Notes: Panels A and B show the age distribution of applicants to the MSCS and OMSCS programs respectively. Panel A includes all 2013 and 2014 MSCS applicants. Panel B includes all spring 2014, fall 2014 and spring 2015 OMSCS applicants. The few applicants with ages below twenty and above sixty (7 and 36, respectively) are rounded to those values for this figure.

Figure 3: Access to and Enrollment in the Online Option

(A) Online Admission



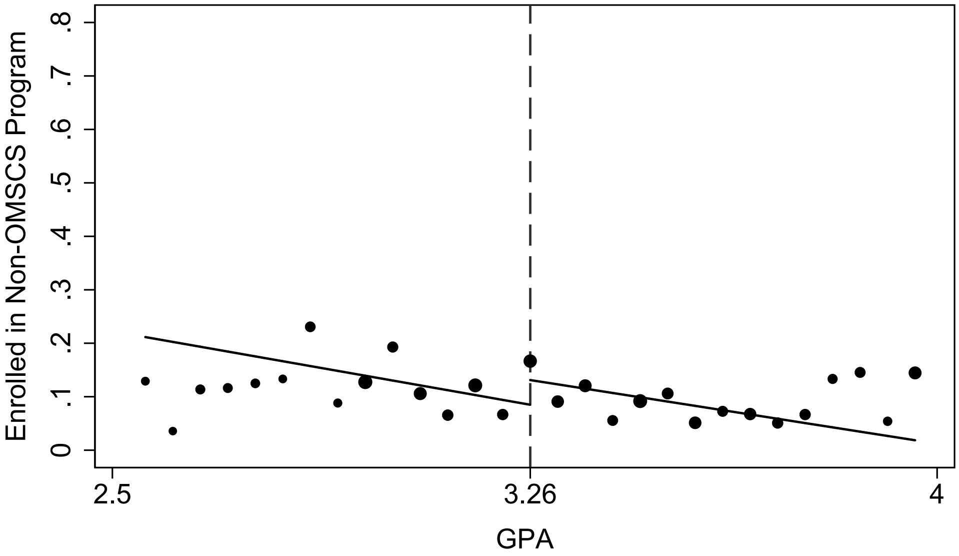
(B) Online Enrollment



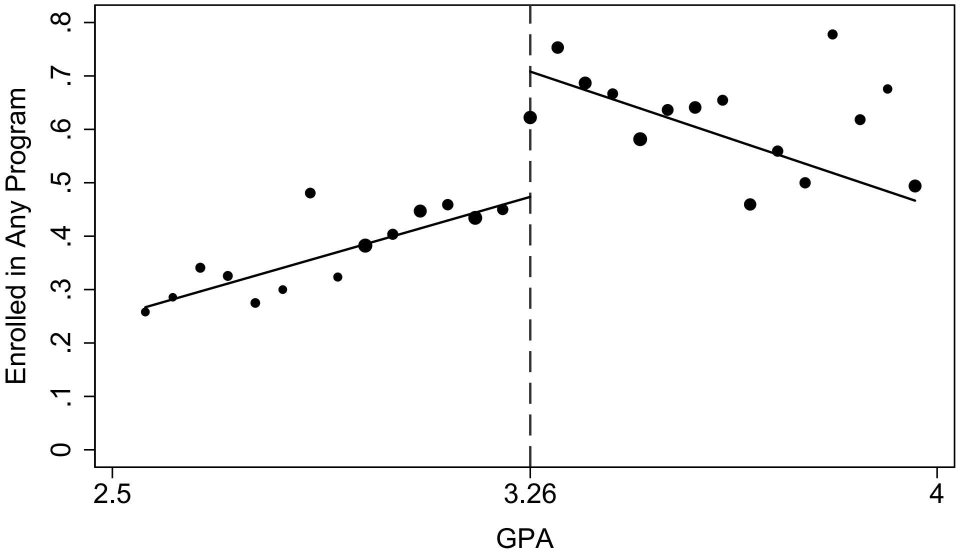
Notes: The above figure shows as a function of college GPA the fraction of spring 2014 OMSCS applicants who were admitted to OMSCS (panel A) and who enrolled in OMSCS by spring 2015 (panel B). The sample is limited to those with GPAs between 2.5 and 4.0. The dots shown come from binning the data in intervals 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.

Figure 4: Enrollment in Other and Any Degree Programs

(A) Enrollment Elsewhere



(B) Enrollment Anywhere



Notes: The above figure shows as a function of college GPA the fraction of spring 2014 OMSCS applicants who by spring 2015 had enrolled in any non-OMSCS program (panel A) and any program, OMSCS or otherwise (panel B). The sample 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.

Table 1: Characteristics of Program Applicants and Enrollees

	All			US		
	OMSCS (1)	MSCS (2)	NSF (3)	OMSCS (4)	MSCS (5)	NSF (6)
(A) Application and enrollment						
Degrees awarded			20,983			10,948
Number applied (annualized)	3,625	1,564		2,715	145	
Number admitted (annualized)	1,997	232		1,521	71	
Number enrolled (annualized)	1,507	124		1,151	32	
Admission rate	0.55	0.15		0.56	0.49	
Enrollment rate	0.42	0.08		0.42	0.22	
(B) Applicant characteristics						
US citizen	0.75	0.09				
Age	35.2	23.9		35.9	25.3	
Employed	0.90	0.50		0.92	0.50	
White	0.53	0.08		0.64	0.58	
Black or Hispanic	0.16	0.02		0.18	0.16	
Asian	0.27	0.89		0.14	0.22	
Female	0.14	0.25		0.13	0.16	
Computer science major	0.39	0.64		0.40	0.58	
(C) Enrollee characteristics						
U.S. citizen	0.76	0.26	0.52			
Age	33.9	24.0		34.4	25.3	
Employed	0.92	0.49		0.93	0.47	
White	0.56	0.26		0.64	0.61	0.54
Black or Hispanic	0.12	0.06		0.12	0.14	0.18
Asian	0.28	0.67		0.20	0.22	0.14
Female	0.12	0.28	0.27	0.12	0.16	0.26
Computer science major	0.46	0.63		0.47	0.65	

Notes: Data in columns 1 and 4 come from spring 2014, fall 2014 and spring 2015 applicants to OMSCS. Data in columns 2 and and 5 come from fall 2013 and fall 2014 applicants to MSCS. Column 3 describes those who completed computer science master's degrees in the US in 2013 and comes from 2013 IPEDS Completion Survey, accessed through the NSF's WebCASPAR site. Columns 1-3 include all individuals, while columns 4-6 limit the sample to American citizens. For comparability, the numbers in columns 1, 2, 4 and 5 of panel A are scaled to be annual.

Table 2: Distribution of Employers for OMSCS Applicants, Admits, and Enrollees

Listed employer	Number of applicants	Percentage of total	Cumulative percentage
AT&T	779	14.3	14.3
Microsoft	55	1.0	15.3
United Parcel Service	45	0.8	16.2
U.S. Air Force	43	0.8	17.0
IBM	35	0.6	17.6
Oracle	35	0.6	18.2
Google	33	0.6	18.9
Cisco Systems	30	0.6	19.4
U.S. Army	27	0.5	19.9
Lockheed Martin	26	0.5	20.4
Hewlett-Packard	25	0.5	20.8
General Electric	24	0.4	21.3
Intel	24	0.4	21.7
Raytheon	23	0.4	22.1
Self-employed	23	0.4	22.6
Northrop Grumman	22	0.4	23.0
Amazon	21	0.4	23.4
Booz Allen Hamilton	17	0.3	23.7
Dell	17	0.3	24.0
Accenture	16	0.3	24.3
Apple	16	0.3	24.6
Boeing	16	0.3	24.8
General Motors	12	0.2	25.1
U.S. Navy	12	0.2	25.3
Verizon	12	0.2	25.5
Employers with 2-11 applicants	885	16.3	41.8
Employers with 1 applicant	2626	48.3	90.1
No employer listed	540	9.9	100.0

Notes: Shown above are the top 25 employers of OMSCS applicants (using data from all three waves), as well as the total number of applicants from employers with 2-11 applicants, from employers with only one applicant, and with no employer listed.

Table 3: College-Level Characteristics of Applicants

	Applicants		Admits		Enrollees	
	OMSCS	MSCS	OMSCS	MSCS	OMSCS	MSCS
Fraction receiving federal grant aid	0.24	0.21	0.23	0.18	0.22	0.17
Six-year graduation rate	0.60	0.68	0.62	0.73	0.62	0.73
SAT math score (75th percentile)	647	675	653	696	655	706
Percent submitting SAT	0.76	0.79	0.76	0.84	0.77	0.86
N	3,592	361	2,122	166	1,594	76

Notes: Shown above are the mean characteristics of the U.S. colleges attended by applicants to OMSCS and MSCS, as derived from the 2005 wave of IPEDS. All differences between OMSCS and MSCS are statistically significant. The table excludes any applicant whose listed undergraduate college could not be found in IPEDS.

Table 4: Access to OMSCS and Enrollment in Higher Education

	Admitted	Enrolled OMSCS		Enrolled elsewhere		Enrolled anywhere	
	(FS)	(RF)	(IV)	(RF)	(IV)	(RF)	(IV)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(A) BW=0.75							
Admissible	0.202***	0.243***	1.203***	-0.013	-0.062	0.217***	1.072***
	(0.059)	(0.052)	(0.199)	(0.029)	(0.132)	(0.038)	(0.236)
(B) BW=0.75, controls							
Admissible	0.211***	0.248***	1.180***	-0.014	-0.068	0.220***	1.046***
	(0.050)	(0.041)	(0.186)	(0.028)	(0.125)	(0.034)	(0.214)
(C) BW=0.5, controls							
Admissible	0.187***	0.222***	1.188***	0.044	0.236	0.247***	1.324***
	(0.066)	(0.051)	(0.271)	(0.033)	(0.236)	(0.041)	(0.398)
(D) BW=0.25, controls							
Admissible	0.226**	0.221***	0.976***	0.094**	0.416	0.269***	1.189***
	(0.089)	(0.077)	(0.221)	(0.044)	(0.333)	(0.059)	(0.383)
(E) BW=IK, controls							
Admissible	0.164**	0.216***	1.209***	0.065	0.269	0.255***	1.499**
	(0.077)	(0.059)	(0.344)	(0.040)	(0.260)	(0.045)	(0.579)
IK Bandwidth	0.38	0.40	0.40	0.30	0.30	0.43	0.43
Control mean	0.41	0.35		0.11		0.44	

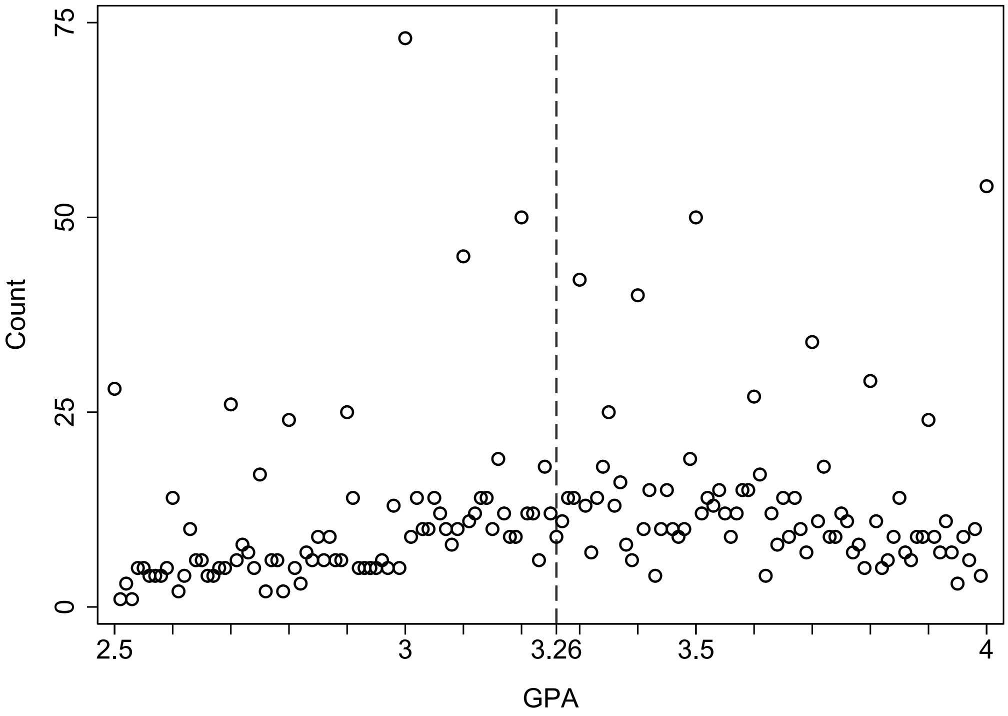
Notes: Heteroskedasticity robust standard errors clustered by GPA are in parentheses (* p<.10 ** p<.05 *** p<.01). Each regression discontinuity estimate in columns 1-4 comes from a local linear model that regresses an indicator for an admission or enrollment outcome on an indicator for being above the GPA threshold of 3.26, distance from that threshold, and the interaction of the two. Columns 5 and 6 contain instrumental variables 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. 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 spring 2015. The sample size in panels A and B is 1,794, in panel C is 1,370, in panel D is 781 and in panel E ranges from 1,051 to 1,293. Listed below each column is the Imbens-Kalyanaraman optimal bandwidth and the mean of the outcome for those 0.01-0.10 GPA points below the threshold.

Table 5: Heterogeneity in Enrollment Impacts of Access to Online Option

	Admitted	Enrolled OMSCS		Enrolled elsewhere		Enrolled anywhere	
	(FS)	(RF)	(IV)	(RF)	(IV)	(RF)	(IV)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Excluding AT&T	0.225***	0.273***	1.214***	0.067*	0.297	0.314***	1.393***
	(0.078)	(0.060)	(0.258)	(0.040)	(0.244)	(0.051)	(0.390)
N	1,062	1,062	1,062	1,062	1,062	1,062	1,062
U.S. citizen	0.157**	0.224***	1.426***	0.024	0.153	0.236***	1.507**
	(0.071)	(0.060)	(0.430)	(0.042)	(0.311)	(0.052)	(0.595)
N	1,193	1,193	1,193	1,193	1,193	1,193	1,193
Age $\geq$ 35	0.309***	0.338***	1.093***	-0.037	-0.119	0.285***	0.921***
	(0.070)	(0.070)	(0.142)	(0.053)	(0.164)	(0.069)	(0.203)
N	668	668	668	668	668	668	668
Age $<$ 35	0.082	0.123	1.492	0.123***	1.492	0.223***	2.708
	(0.088)	(0.076)	(1.119)	(0.034)	(1.761)	(0.076)	(2.430)
N	697	697	697	697	697	697	697
Male	0.161**	0.226***	1.406***	0.030	0.184	0.240***	1.489**
	(0.071)	(0.055)	(0.414)	(0.040)	(0.304)	(0.046)	(0.588)
N	1,184	1,184	1,184	1,184	1,184	1,184	1,184
Female	0.362**	0.195	0.539**	0.172*	0.474	0.339**	0.936**
	(0.140)	(0.130)	(0.255)	(0.103)	(0.355)	(0.141)	(0.359)
N	181	181	181	181	181	181	181
White or Asian	0.218***	0.247***	1.130***	0.060	0.275	0.289***	1.322***
	(0.069)	(0.058)	(0.215)	(0.037)	(0.234)	(0.050)	(0.339)
N	1,067	1,067	1,067	1,067	1,067	1,067	1,067
Black or Hispanic	0.040	0.042	1.033	0.060	1.477	0.026	0.656
	(0.114)	(0.112)	(2.345)	(0.093)	(4.996)	(0.120)	(2.627)
N	243	243	243	243	243	243	243

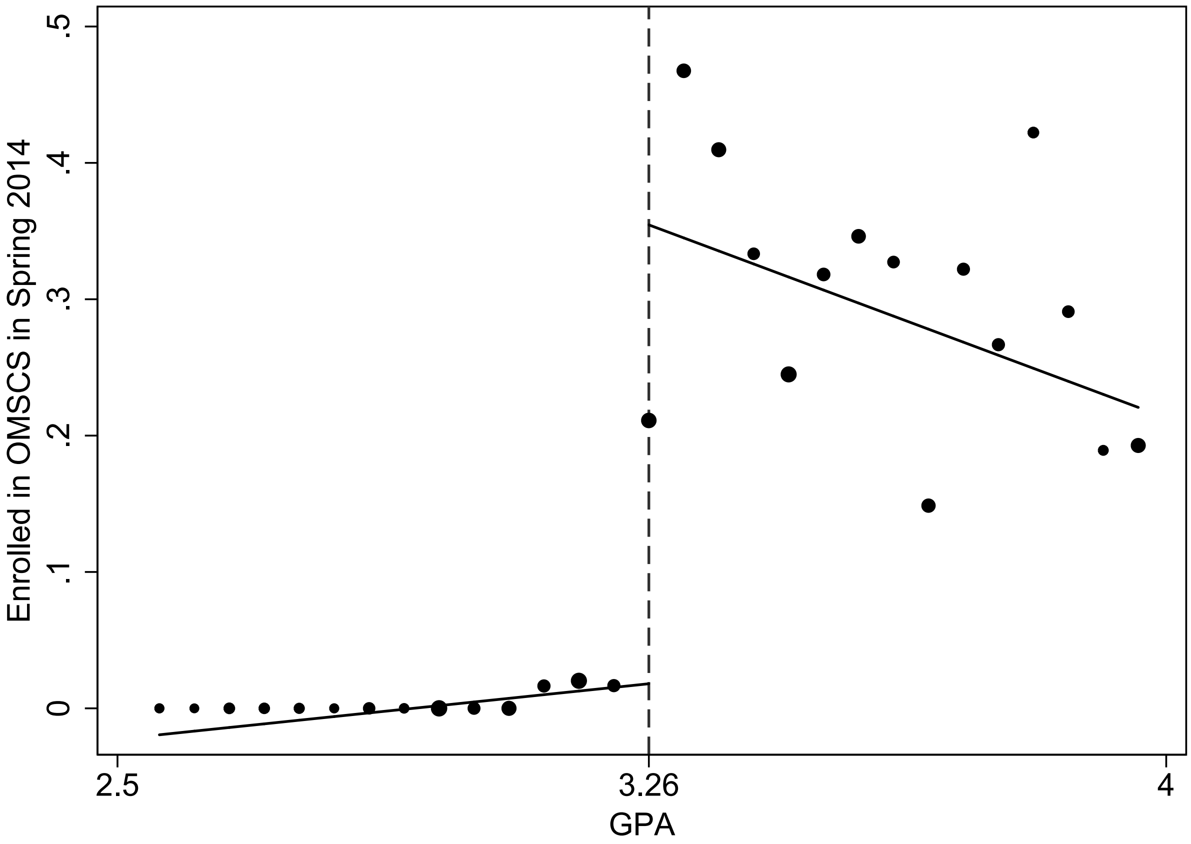
Notes: Heteroskedasticity robust standard errors clustered by GPA are in parentheses (* p<.10 ** p<.05 *** p<.01). Each regression discontinuity estimate in columns 1-4 comes from a local linear model that regresses an indicator for an admission or enrollment outcome on an indicator for being above the GPA threshold of 3.26, distance from that threshold, and the interaction of the two. Columns 5 and 6 contain instrumental variables 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 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 A.1. Enrollment is measured by spring 2015.

Figure A.1: GPA Distribution, Initial OMSCS Applicants



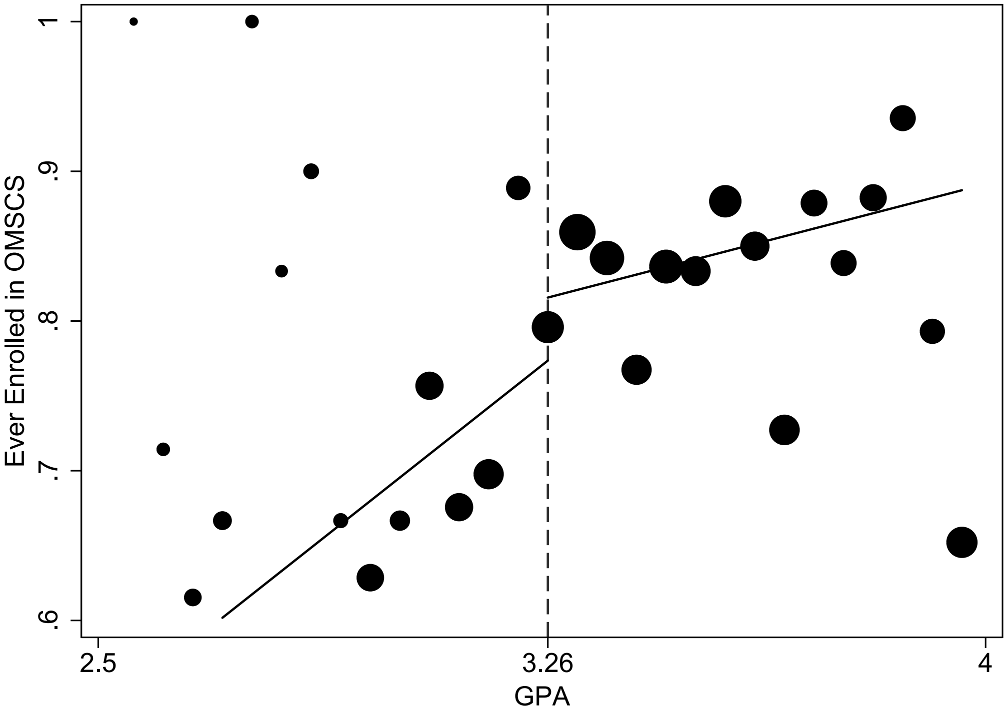
Notes: The above figure shows the number of spring 2014 OMSCS applicants with a given GPA, limiting the sample to those with GPAs between 2.5 and 4.0.

Figure A.2: Immediate Enrollment in the Online Option



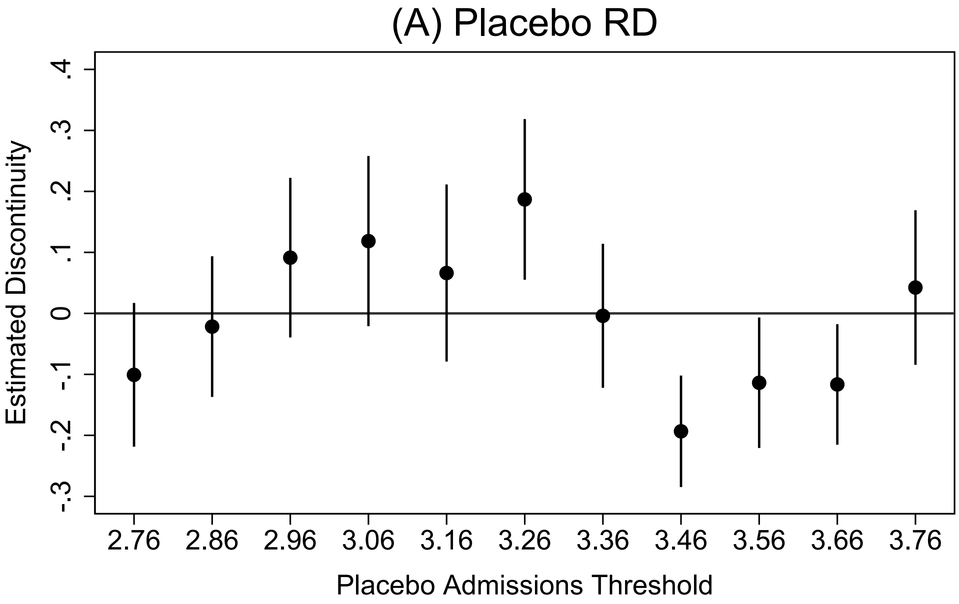
Notes: The above figure shows as a function of college GPA the fraction of spring 2014 OMSCS applicants who enrolled in OMSCS in spring 2014. TThe sample is limited to those with GPAs between 2.5 and 4.0. The dots shown come from binning the data in intervals of 0.05 from the threshold, with dot size 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.

Figure A.3: Enrollment in the Online Option, Conditional on Admission

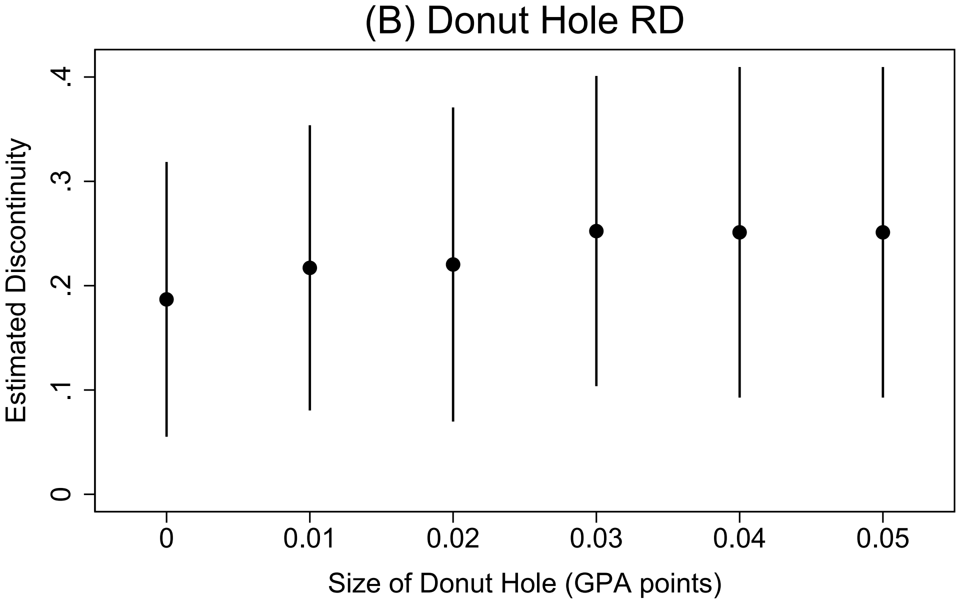


Notes: The above figure shows as a function of college GPA the fraction of spring 2014 OMSCS applicants who were admitted to OMSCS and who enrolled in OMSCS by spring 2015. The sample is limited to those with GPAs between 2.5 and 4.0. The dots shown come from binning the data in intervals of 0.05 from 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 0.4.

Figure A.4: Placebo and Donut Hole Tests: Online Admission



(A) Placebo RD

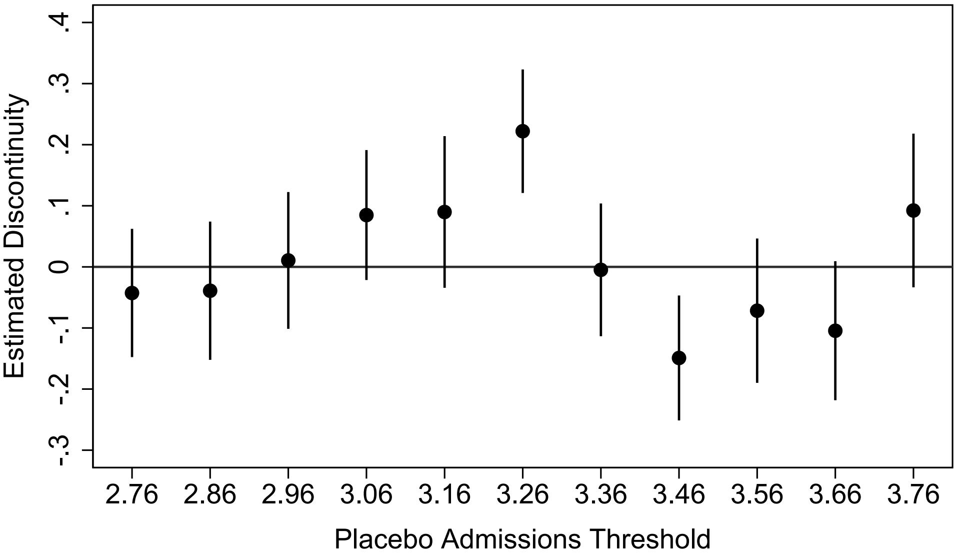


(B) Donut Hole RD

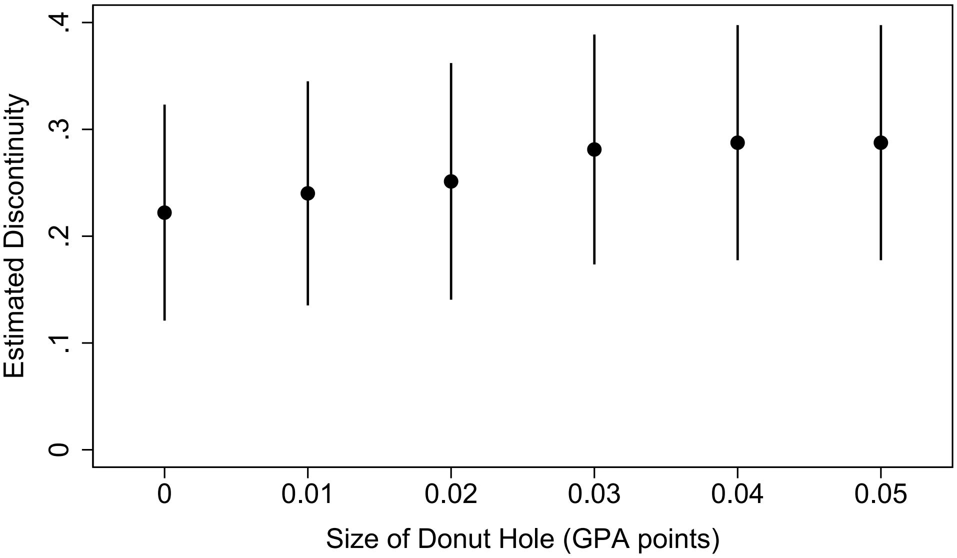
Notes: The outcome in all regressions shown is admission to OMSCS, for spring 2014 OMSCS applicants. Panel A shows estimated discontinuities from regression specifications that assume the admissions threshold is at the listed GPA value, using a bandwidth of 0.5 GPA points and including demographic controls. Panel B shows estimated discontinuities from regression specifications that assume the correct threshold of 3.26, that use a bandwidth of 0.5 GPA points and include demographic controls, but that exclude applicants whose GPAs are within the listed distance of the threshold. Vertical lines indicate 95% confidence intervals.

Figure A.5: Placebo and Donut Hole Tests: Online Enrollment

(A) Placebo RD



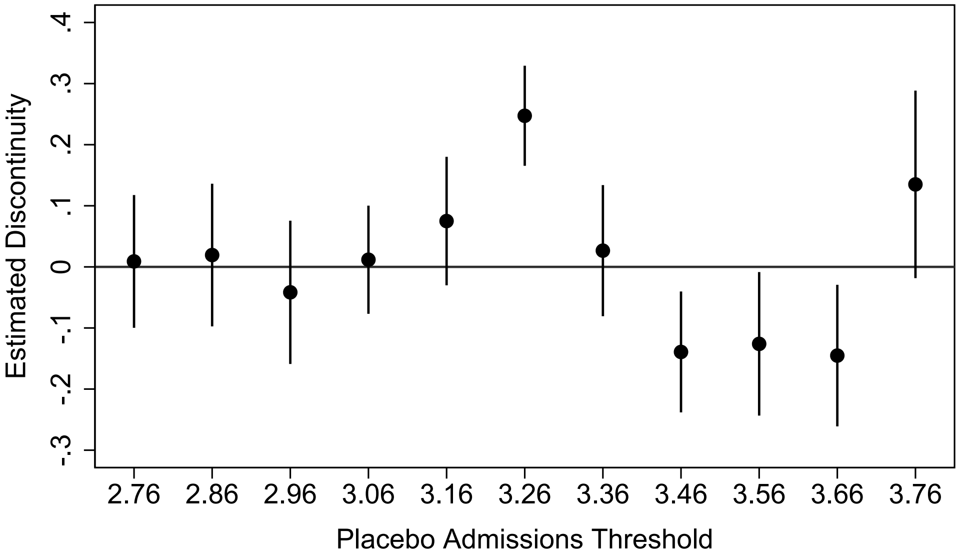
(B) Donut Hole RD



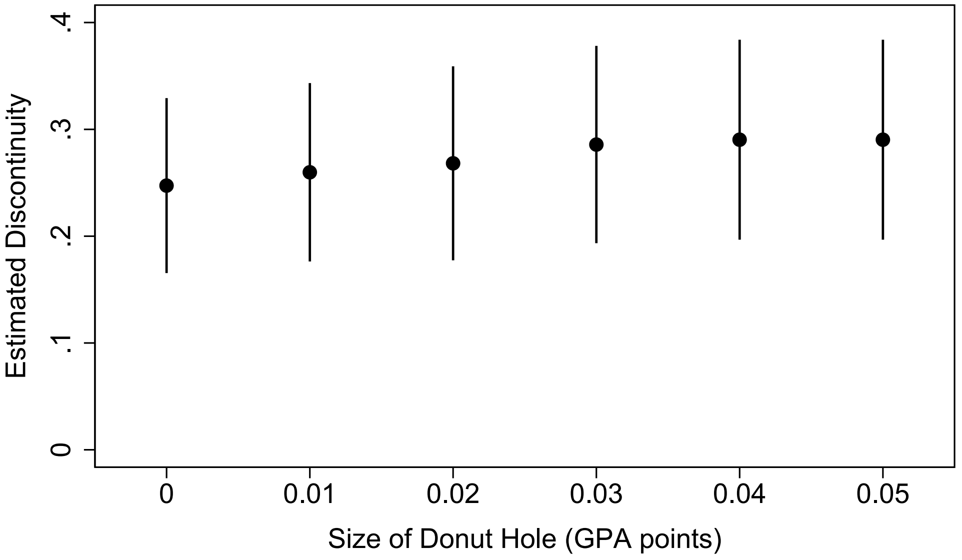
Notes: The outcome in all regressions shown is enrollment in OMSCS by spring 2015, for spring 2014 OMSCS applicants. Panel A shows estimated discontinuities from regression specifications that assume the admissions threshold is at the listed GPA value, using a bandwidth of 0.5 GPA points and including demographic controls. Panel B shows estimated discontinuities from regression specifications that assume the correct threshold of 3.26, that use a bandwidth of 0.5 GPA points and include demographic controls, but that exclude applicants whose GPAs are within the listed distance of the threshold. Vertical lines indicate 95% confidence intervals.

Figure A.6: Placebo and Donut Hole Tests: Enrollment Anywhere

(A) Placebo RD



(B) Donut Hole RD



Notes: The outcome in all regressions shown is enrollment in any degree program by spring 2015, for spring 2014 OMSCS applicants. Panel A shows estimated discontinuities from regression specifications that assume the admissions threshold is at the listed GPA value, using a bandwidth of 0.5 GPA points and including demographic controls. Panel B shows estimated discontinuities from regression specifications that assume the correct threshold of 3.26, that use a bandwidth of 0.5 GPA points and include demographic controls, but that exclude applicants whose GPAs are within the listed distance of the threshold. Vertical lines indicate 95% confidence intervals.

Table A.1: OMSCS and MSCS Applicant Characteristics by Cohort

	O spring 2014 (1)	O fall 2014 (2)	O spring 2015 (3)	O fall 2015 (4)	O spring 2016 (5)	OMSCS fall 2016 (6)	MSCS fall 2013 (7)	MSCS fall 2014 (8)	MSCS fall 2015 (9)	MSCS fall 2016 (10)
(A) Gender, race										
Male	0.86	0.86	0.86	0.84	0.84	0.84	0.76	0.75	0.75	0.75
White	0.54	0.55	0.50	0.00	0.00	0.00	0.08	0.08	0.05	0.05
Black or Hispanic	0.18	0.14	0.16	0.08	0.00	0.00	0.02	0.03	0.02	0.02
Asian	0.24	0.28	0.31	0.00	0.00	0.00	0.90	0.88	0.93	0.93
(B) Geography										
Georgia Resident	0.14	0.14	0.13	0.00	0.00	0.00	0.04	0.03	0.02	0.02
Resides in US	0.91	0.88	0.90	0.00	0.00	0.00	0.11	0.13	0.08	0.09
US citizen	0.78	0.73	0.71	0.00	0.00	0.00	0.09	0.10	0.06	0.07
US perm res	0.07	0.07	0.09	0.00	0.00	0.00	0.01	0.01	0.01	0.02
Foreign citizen	0.15	0.20	0.21	0.00	0.00	0.00	0.90	0.89	0.93	0.91
(C) Age, employment										
Age	36.72	33.87	34.00	32.24	33.08	32.00	23.66	24.07	23.80	.
Employed	0.91	0.90	0.88	.	.	.	.	0.50	.	.
Employed by AT&T	0.23	0.09	0.06	.	.	.	.	0.00	.	.
(D) College major										
Computer science	0.43	0.37	0.35	0.36	0.00	0.00	0.66	0.62	0.64	0.61
Engineering	0.27	0.28	0.29	0.30	0.00	0.00	0.26	0.29	0.30	0.30
Other	0.30	0.35	0.36	.	.	.	0.08	0.08	.	.
(E) Admission										
Admitted to GA Tech	0.48	0.62	0.59	0.35	1.00	1.00	0.13	0.16	0.13	0.00
Enrolled in GA Tech	0.39	0.44	0.42	.	.	.	0.07	0.09	.	.
N applied	2,419	1,633	1,386	1,472	1,347	1,972	1,379	1,749	1,925	2,350
N admitted	1,150	1,018	821	508	1,347	1,972	185	279	247	0
N enrolled	953	724	585	1,472	1,347	1,972	96	152	1,925	2,350

Notes: Listed above are mean values of key variables for applicants to the OMSCS and MSCS programs. Enrollment in Georgia Tech refers to enrollment at any time after application through spring 2015.

Table A.2: Covariate Balance Tests

	Male (1)	Asian (2)	Black or Hispanic (3)	U.S. citizen (4)	Age (5)	Employed (6)	Majored in CS (7)
(A) BW = 0.75							
Admissible GPA	0.028	0.048	-0.009	-0.030	-1.475	0.011	-0.064
	(0.029)	(0.030)	(0.028)	(0.030)	(1.039)	(0.023)	(0.059)
N	1,795	1,795	1,795	1,795	1,795	1,795	1,795
(B) BW = 0.5							
Admissible GPA	0.031	0.050	-0.024	-0.035	-1.929	-0.003	-0.113
	(0.035)	(0.033)	(0.033)	(0.034)	(1.223)	(0.027)	(0.073)
N	1,365	1,365	1,365	1,365	1,365	1,365	1,365
(C) BW = 0.25							
Admissible GPA	0.015	0.067	-0.058	-0.056	-3.287*	-0.007	-0.048
	(0.054)	(0.049)	(0.043)	(0.051)	(1.731)	(0.039)	(0.104)
N	776	776	776	776	776	776	776
(D) BW = IK							
Admissible GPA	0.002	0.060	-0.025	-0.044	-1.703	-0.015	-0.139*
	(0.046)	(0.039)	(0.038)	(0.039)	(1.315)	(0.030)	(0.077)
N	1,061	1,061	998	1,122	1,266	1,183	1,266
Bandwidth	0.35	0.35	0.34	0.39	0.45	0.41	0.45
Control mean	0.86	0.13	0.20	0.88	37.13	0.91	0.50

Notes: Heteroskedasticity robust standard errors clustered by GPA are in parentheses (* p<.10 ** p<.05 *** p<.01). Each regression discontinuity estimate comes from a local linear model that regresses the covariate listed on an indicator for being above the GPA threshold, distance from that threshold, and the interaction of the two.The sample includes all spring 2014 applicants to OMSCS whose GPA is within the listed bandwidth. Panel D uses Imbens-Kalyanaraman optimal bandwidths. Listed below each column is the mean of the covariate for those 0.01-0.10 GPA points below the threshold.