Are Online Degrees Substitutes for Traditional Degree Programs? Evidence from a Correspondence Study

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Abstract

This paper uses a correspondence study to examine how completing a degree online affects labor market outcomes. As part of the study, fictional resumes are used to apply to real job openings while varying the reported medium of instruction (online or traditional/in-person). The outcome of interest is the number of callbacks for interview. Fictional applicants who report having a traditional degree receive almost twice as many callbacks as those who report an online degree, even though assignment to each type of degree was random. These findings suggest that completing an online degree would limit the labor market prospects of typical college-age students.

Introduction

In 2014, 5.8 million U.S. students were taking at least one college class online and 2.85 million students were taking only online classes (Allen et al., 2016). The same source reports that the number of students taking some or all of their college classes is growing by about 4% per year. While only a fraction of these students are in the typical undergraduate student demographic the growth of online classes as a medium of instruction naturally raises several questions: what is higher education going to look like 20 years from now? Will all students be taking at least some classes online? Will the modal student attend any face-to-face classes?

The answer to these questions surely depends on whether or not online classes are seen as valuable by students and potential employers. Despite this, the literature on online coursework appears to be stuck on measuring how taking classes online affects human capital accumulation. Researchers in this area find that student learning (measured in a variety of ways) is affected mildly or not at all by the medium of instruction: Bennett et al. (2007), Ary and Brune (2011), Hernandez-Julian and Peters (2012), Figlio et al. (2013), and Bowen et al. (2014) are just a few examples. A notable exception to this pattern is Alpert et al. (2016) who find that learning outcomes for students in an online section were lower by between 5 and 10 points (out of 100) on a cumulative microeconomics final exam. Regardless, the literature has either ignored the effect online education might have on labor market success or implicitly assumed that any effect is captured by learning outcome differences.

In contrast, this paper uses a correspondence study to examine outcomes for those with online degrees. In a correspondence study, resumes which randomly vary one or more characteristics of interest are sent to employers and callbacks for interview are tracked. While callbacks are not a perfect measure of labor market success, the assumption is that applicants with more job interviews will face shorter spells of unemployment and ultimately earn higher wages.

The experimental set up, described in greater detail in Section , creates a pool of resumes and associated cover letters.[1] For each resume the dates, names, contact information, address, and previous employer names and locations are altered so as not to be representative of any real applicant. Resumes are then randomly assigned to either convey that the fictional job candidate's degree was obtained via a specific university's online ”wing” or in a traditional classroom setting. To signal an online degree the word “online” was added to the resume in parentheses next to the name of the college or university. It is possible that some employers did not notice this alteration, which would suggest that the findings of this paper represent a lower bound on how online degrees affect callbacks for interview.

While telling an employer that an applicant has a degree earned online may seem contrived, a 2010 survey by the Society of Human Resource Managers found that only 17% of Human Resource Professionals had never seen an applicant clearly indicate an online degree.[2] This does not mean that all job applicants who have an online degree always choose to reveal that information to

[1]Phone numbers and emails are created for each fictional individual via a well-known internet service provider.

[2]See http://www.shrm.org/research/surveyfindings/articles/pages/hiringpracticesandattitudes.aspx. In the years since that survey, the number of people completing online classes and degrees has risen considerably. See http://nces.ed.gov/pubs2014/2014023.pdfandhttps://nces.ed.gov/fastfacts/display.asp?id=80 for more details.

prospective employers. However, it eases concerns that the resumes in this study will stand out as unique and/or unusual: unique resumes might bias employers in ways that are unrelated to the their opinion of the capability of the applicant.

Fictional applicants' resumes and cover letters were then used at random to apply to real jobs across dozens of U.S. cities. First, positions for which any resume within a group (nursing, engineering, accounting, and so on) could apply for were identified from an online jobs posting board. Then, each identified available position received an application chosen at random from within the relevant group. That application could reflect either an online degree or a traditional degree.[3] After a resume is sent, requests (phone calls and emails) for interview are tracked.[4]

Note that the experimental variation used in this paper is not designed to compare students who earn a degree at selective traditional universities to the outcomes of students at for-profit schools like the University of Phoenix or DeVry. For-profit schools do not primarily serve the population that the paper is focused upon: "traditional" students (defined as young adults who attend college shortly after graduating from high school). For the same reason, the paper is not focused on the benefits of online degree programs for non-traditional students, such as those who are retraining after several years in the workforce. For many of those students the choice is between an online degree and no degree rather than between a traditional degree and an online degree (see Darolia et al., 2015 and Deming et al., 2016).

Instead, the paper examines outcomes for students who earn online and traditional degrees at established universities and colleges. Many well-known schools have a significant online presence offering dozens of completely online degrees including Arizona State, Ohio State, Penn State, Northeastern University, and many more. While only a small fraction of the students currently enrolled in these kinds of programs are typical college-age students who voluntarily choose to do a degree online rather than in person, the paper asks what the consequences might be for students who choose that route. This allows the paper's findings to contribute to the existing literature on learning outcomes in online settings for these same kinds of students.

[3] Each resume was used for about 20 completed applications. There is variation in the total number of applications sent for each individual due to the random process used to select resumes for a given position. Occasionally, an application became unusable after the application was submitted due to a canceled search, a position being filled internally, and so on.

[4] Note that if a request for interview is received the employer is contacted as soon as is feasible to thank them and politely decline the request.

In the data, the negative effect of an online degree is large. Estimates suggest that traditional degree holders are almost twice as likely to be called back. To provide some context, the magnitude of this effect is as large or larger than effects seen in correspondence studies examining callback rates by race, gender, and age.[5] The obvious take-away for job applicants, who have a degree earned online, is not to inform employers about the medium of instruction. However, that is only helpful to online degree holders' job prospects if employers would not find out the information later in the hiring process. Moreover, a similar argument applies to all correspondence studies: for example, the takeaway from Kroft et al. (2013) would be to somehow hide spells of unemployment from employers.

The paper proceeds with a reviews of the literature on the relative merits of online education along with the benefits and drawbacks of using correspondence studies in Section . Section describes the correspondence study procedure in detail. Section summarizes the data and checks on the experimental randomization. Section provides the main estimates and considers their robustness. Section concludes.

Relevant Literature

Lack (2013) provides an exhaustive review of the available research on learning outcomes in online education through the end of 2012. The review details large and small studies in several areas including sociology (Driscoll et al., 2012), accounting (Rich and Dereshiwsky, 2011), management (Daymount and Blau, 2008), and engineering (Enriquez, 2010). Lack's review finds no evidence that students, controlling for observable characteristics, learn less effectively when the medium of instruction is online rather than in-person. Unfortunately, the conclusions that can be drawn from these studies are complicated by differences in research methods, subject attrition, treatment and control group cross-contamination, small sample sizes, different populations of interest, along with each study having a unique institutional setting and time-frame.

Since Lack's review a number of studies with larger sample sizes and controlled variation have been published. Figlio et al. (2013) examine of the effects of watching online rather than attending introductory economics lectures at a large selective research institution in the United States. The

[5]Estimates are based on 1,891 job applications using 100 unique resumes.

authors find only mild support for the hypothesis that learning outcomes are inferior in online settings. In the study, students were randomly assigned to taking introductory microeconomics online versus in-person. The authors observe that regardless of sex or race, average test scores were higher for those who were assigned to face-to-face instruction. However, the effects were modest and not always statistically different from zero.

Bowen et al. (2014), in a larger-scale study, allow for online instruction to be augmented by a new interactive learning platform. They perform their experiment at six large universities, randomly assigning undergraduates into traditional and hybrid statistics classes. The hybrid classes met once per week. Students accessed sophisticated machine-guided instruction instead of a second weekly class meeting. Bowen et al. find that "students in the hybrid format are not harmed by this mode of instruction in terms of pass rates, final exam scores, and performance on a standardized assessment of statistical literacy." Alpert et al. (2016) also find that students in a hybrid class do as well as those in classes that follow a traditional twice-weekly meeting schedule.

While the research on learning outcomes in single classes suggests that online coursework might be a valid alternative to traditional in-person instruction, no study has been able to examine how a purely online degree program affects learning outcomes relative to a traditional degree.[6] More problematically, the existing work on this topic implicitly assumes that the right metric for judging the success or failure of online coursework is human capital accumulation as measured by performance on assignments and examinations. For example, Figlio et al. suggest "[i]nternet-based classes may even dominate live-lecture classes, as they offer students more flexibility in the timing of attendance as well as the opportunity to review lectures to clear up confusing points." Of course, labor market outcomes would be impossible to convincingly relate to a change in the mode of instruction of a single college course. However, that doesn't mean labor market outcomes should be ignored.[7]

The lack of discussion and rigorous research on the impact of online education on labor market

[6] To be fair, to validly examine the outcomes from entirely online programs versus traditional degrees, experimental variation at a higher level would be required. However, volunteer subjects would likely form a small and unique group and students who were randomly assigned into online degrees may take other steps to mitigate its effects over a period of four or more years. In any case, such a study, given the significance of the intervention it entails, would be unlikely to obtain approval from an Institutional Review Board.

[7] Rechlin and Kraiger (2012) appear to be the only authors who have considered this issue. However, their study examines the attitudes of just 23 employed Industrial-Organization (I-O) Psychologists towards job applicants who have completed a psychology degree online and demand effects bias their survey instrument.

outcomes motivates this paper. The fact that information on the medium of instruction is not recorded by labor market surveys means that a correspondence study is likely the only way to causally relate the attitudes of real employers towards potential employees with degrees that are earned online. Correspondence studies are seen as a reliable solution when crucial information available to employers is not available to or cannot be controlled for by researchers. Bertrand and Mullainathan (2004) provide the ideal example of the value and purpose of such studies. The authors were interested in the perennial question of how race affects labor market outcomes. In particular, they wanted to know if employers screen resumes using indicators for race (such as names). Their paper's title "Are Emily and Greg More Employable than Lakisha and Jamal?" provides the clearest illustration of their approach. Bertrand and Mullainathan find that white-sounding names received 50 percent more callbacks for interview, all else equal. However, they focused only on low-skilled positions. Because the data in this paper also includes resumes with ethnic applicant names it can extend Bertrand and Mullainathan's findings to positions for which a bachelor's degree is required. As a preview, estimates suggest a difference in callback rates between races persists for higher-skilled positions but the difference is not as large as Bertrand and Mullainathan estimated for low-skilled positions (see Section 5).

This paper's approach and research question are complementary to Darolia et al. (2015) and Deming et al. (2016). Each examines how for-profit degrees (employers are left to infer that many of these are delivered online) are viewed by employers using a correspondence study. Darolia et al.'s findings suggest a for-profit college education is no better (in terms of receiving callbacks for interview) than community college or no college at all. Deming et al. find that for-profit degrees earn slightly fewer callbacks than degrees from non-selective public institutions. Both studies examine low-prestige institutions comparing public non-profit to private for-profit degree programs. Moreover, neither emphasize the separate role of online education as a medium of instruction. This paper is also different in that focuses on established selective schools that offer both in-person and online versions of the same degree and how associated outcomes vary for typical college students.

Lastly, while not directly examining the effects of college reputation on labor market outcomes, this paper makes a contribution to that literature. Dale and Krueger (2014) provide a detailed analysis of the literature and find that reputation, proxied by selectivity, positively affects labor market outcomes in regressions. However, after controlling for selection *into* selective colleges, the effects fall dramatically. Research on this topic is usually based on differences *between* schools. On the other hand, this paper can be viewed as examining *within*-school variation in reputation created by offering online degree programs.

Acknowledging the Limits of Correspondence Studies

Correspondence studies are an excellent way to uncover the attitudes of employers towards specific employee characteristics. However, a number of caveats apply. Firstly, callbacks for interviews do not pay bills, and it is not clear from these studies that fewer callbacks actually translates to lower wages and higher unemployment. Instead, the information transmitted to employers via the resume may improve matching, reducing wasteful and unnecessary interviews that would not result in a job offer anyways. In addition, the revelation of some characteristics perhaps allows an applicant to gain access to an interview they would not have otherwise earned that ultimately leads to an ideal job offer. Some employers, due to their own personal experiences may be seeking black, female, older, or homosexual workers, or might take pity (for lack of a better word) on those with longer spells of unemployment if they themselves faced a similar spell of unemployment. Certain characteristics might reduce the number of callbacks but increase the probability of getting the "right" callback.

Secondly, given employers must review resumes quickly, experimental variation may not be as strong as it seems in a correspondence study set up. If employers fail to notice the experimental variation it would limit differences in callback rates between applicants. This would mean that any estimate of the effect of some characteristic on callbacks is actually only a lower bound.

Thirdly, applying for jobs posted in newspapers and online is only one way to secure employment. Social networks and connections, internships, and personal recommendations may compensate for or exacerbate the effects seen in correspondence studies. It is not clear that an individual who fares poorly in a correspondence study couldn't improve their potential job opportunities via alternative approaches to job search.

Additionally, correspondence studies cannot be sure that their experimental variation does not interact with employers' (or their agents') priors based upon experience. Take Bertrand and Mullainathan's paper as an example. The paper claims to study the effect of having a black-sounding name compared to an identical resume with a white-sounding name. However, to be strict, their paper studies the effect of having a black-sounding name, reporting it without alteration (Jamal Jones could easily present himself on his resume as Jay or J. Jones) *and* having a resume that does not reflect changes that an employer may *expect* to see given that variation. That is, non-fictional white males and black males might present very different resumes even if they had similar work histories and education. If resumes from otherwise similar whites and blacks are systematically different in the population, those differences are part of the experimental variation. In such a case, the effect reported in the paper is the combined effect of having a black-sounding name but having a resume that doesn't seem like other resumes from black applicants. This example is not chosen at random: Bertrand and Mullainathan find that white applicants experience a much higher return to increased resume quality which suggests employers may be skeptical of high-quality black resumes.

Kroft et al. (2013)'s resume study on the effects of unemployment duration on callbacks is subject to a similar critique. The authors are identifying not just the effect of unemployment duration but the combined effect of being unemployed and being foolhardy enough to not have a good (even if contrived or completely fabricated and even if the employer *knows* that it is fabricated) *explanation* for the spell of unemployment.

This paper is subject to the same unavoidable criticism. Therefore, the estimates reported later in the paper should be accurately seen as the impact on callbacks for interview from having an online degree *and* telling the employer about it. However, the consequences of this distinction are unclear. Even if an applicant does not mention the online nature of their education in the resume, the issue will likely come up during an interview. Consider an applicant who lists work experience coincident with their college degree in another state. Alternatively, the fact a degree was completed online likely will arise when the candidate is asked to answer location-specific questions at interview. This means that while the effects of unemployment duration on callbacks and eventual employment may perhaps be eliminated with a simple one sentence explanation, the effect of online degrees on labor market success is less avoidable. Alternatively, mimicking the concerns with Bertrand and Mullainathan's approach, employers may be used to applicants with online degrees taking steps to compensate for their perceived deficiency via improvements in other areas. While the resumes may appear equivalent to the researcher, employers may have priors that vary for these kinds of candidates. These issues are considered in Section by examining how the effect of on-line education varies with respect to compensating factors such as GPA and work experience. Intuitively, the idea is that if employers are expecting to see something to compensate for having an online degree - more work experience or a higher GPA - that they do not see, the returns to these will differ for those with online and traditional forms of college education.

These methodological caveats, while relevant, do not completely invalidate the correspondence study method nor the causal relationships uncovered. Instead, they should be viewed as qualifications, adding a disclaimer that delineates what it is that is being explained and how it might be interpreted differently under alternative circumstances.

Experimental Procedure

The procedure to generate resumes is similar across correspondence studies. For authenticity, a pool of resumes is created from sample resumes researchers find online. These are then deconstructed, anonymized, and reconstructed manually or via a computer program (see Lahey and Beasley, 2009). The resumes are then sent to real jobs advertised online or in newspapers that the resume is qualified for. Critically, before the resumes are sent, they are randomly assigned one of n possible variations in a characteristic of interest. The researcher then tracks callbacks for interview to infer causal relationships between each variation and labor market outcomes.

Because the randomization is orthogonal, by construction, to other characteristics, differences in callbacks can be considered causally-related to the associated experimental variation. This paper uses a similar approach but differs in an important dimension. Correspondence studies tend to focus on clerical, retail, and administrative roles to ensure they can apply to many job openings with multiple resumes. This study is focused on differences in callbacks for those who have bachelor's degrees. As a result, entry-level clerical and retail jobs are not realistic options. Instead, the paper focuses on several early career positions suitable for recently graduated degree holders in the business, engineering, IT, and medical professions. These fields were chosen because these positions represent the types of jobs associated with degree programs offered online at many institutions, a bachelor's degree in these fields is linked to employment in a particular well-defined job (such as software engineer, nurse, accountant, or business analyst as opposed to english, history, and sociology), and there are typically lots of jobs advertised in these fields. A disclaimer that the findings may not generalize to other situations and professions applies, even though there is no reason to suspect that is the case.

Resume and Profile Generation

A major job-hunting website was used to gather publicly-posted resumes of recent graduates of degree programs in business administration, marketing, accounting, nursing, along with software, mechanical, or manufacturing engineering (for the reasons laid out above). Only resumes representing those who are recent graduates (obtained their BA/BS three or fewer years prior to application) were selected as the growth of online education is a relatively recent phenomenon. All the resumes selected reflect someone who was currently employed in a job that matched their educational background.

The resumes chosen varied in almost every way one can imagine. The individuals lived in a variety of locations, had different work experience, attended different colleges throughout the US, had various degree titles (even within the same field), many listed internships or part-time employment in college, and some used personal statements and listed "headline" keywords while others did not. For practical reasons, the resumes chosen were limited to those currently employed (and therefore having at least *some* experience) to allow a sufficient number of applications to be completed. Openings suitable for recent graduates with *no* experience are rare whereas those requiring one year of experience are relatively plentiful. It is open to debate, but it is likely that examining outcomes for those with no experience would see a similar or larger gap in callback rates if enough suitable openings could be identified.

Once the set of resumes were chosen, they were anonymized by altering names, state of residence, dates and places of employment, college attended, graduation dates, listed GPA, and any remaining identifying characteristics unique to the resume. The estimates in the paper rely on callbacks for 1,891 completed applications using exactly 100 different resumes.[8] Fifty of the resumes created reflected only Caucasian applicants (with names like Matthew, David, Katie, and Jessica accompanied by last names of european origin such as Smith, Mueller, Allen, and Schwartz). Of the other 50, 25 convey that the applicant is African American (with names like DeShawn,

[8]Because these are not low-skill jobs, completing applications is time-intensive.

Shanice, and Jasmine accompanied by last names such as Wilson, Jackson, and Jones) and 25 are identifiably Latin American (with names lime Juan Pablo, Agustin, Gabriela, and Sofia accompanied by last names like Lopez, Gomez, Fernandez, and Ximenez).[9] The perceived gender, degree held (but not the institution), current job title (but not employer name), and years of work experience reported on the resume were not altered. The changes were intended to protect identities while preserving the overall authenticity and quality of the resume.

Each fictional resume listed that the individual attended a university where the degree they earned was offered in both a traditional and an online-only format. As just one example, Penn State University offers 24 degree programs that can be completed online from anywhere in the world.[10] Like many others, the Penn State World Campus FAQ page emphasizes that admissions standards are the same as for the rest of Penn State and that a transcript for an online degree will not be any different to the transcript of those who completed their degree on-campus.[11] Because the degree program was offered both online and in a traditional format, the paper's experimental variation could be applied to the resumes at random.

Next, appropriate email addresses were created (generally: first name, middle initial, last name "at" some internet domain, or a slight variation if that was not available). The email addresses were then associated with "virtual" phone numbers and voice-mail services. The outgoing voice-mail message was left as the default computerized greeting. That is, any message an employer heard when calling was the same regardless of resume received and only differed by phone number.

Lastly, after this process was complete, the details of each resume were recorded into a spreadsheet. A random number between zero and one was then assigned to the resume. Resumes whose random number turned out to be below the median in an ordered list were assigned to report a online degree. That information was conveyed to potential employers by just one word following the name of the university or college the individual graduated from. On a resume this appeared as "[Name of University or College] (online)." That is the only difference potential employers would see on an applicant's resume.[12] Note that this process requires that for each fictional resume, the type of education received did not vary across applications. In addition, because these jobs are not

[9]Names were selected from several lists of historically popular names found online.

[10]The programs offered at Penn State's World Campus can be accessed via http://www.worldcampus.psu.edu.

[11]For example, see the University of Florida's UFOnline FAQ page at http://ufonline.ufl.edu/resources/faqs/.

[12]A sample is provided in Appendix A.

low-skill, each application was accompanied by a cover letter. This is unusual in correspondence studies. Indeed, this paper appears to be the first to attempt a correspondence study that focuses on exclusively higher-skilled positions. The process used to generate cover letters is described in the next subsection.

Cover Letter Generation

Job postings for skilled positions typically request and almost always allow a cover letter. For each resume, a cover letter was created which slightly varied in content across workers but not in organization or intent. All cover letters contained four paragraphs. The first expressed interest in the available position. The second explained the candidate's current role, responsibilities, length of tenure, and expressed a desire to further their career in a new position. The third paragraph explained why the candidate would be a good fit for the available position but was not tailored to each position. Instead, the paragraph reminded the reader of the candidate's education along with their excellent technical, analytical, communication, or other skills as relevant to the field.[13] The final paragraph reiterated the candidate's interest in the position, and expressed a desire to discuss the position at interview. A sample cover letter and associated resume can be found in Appendix A.

Applying to Open Positions and Monitoring Callbacks

As mentioned earlier, a list of positions suitable for all fictional candidates with the same degree was created by searching online job posting boards on a variety of dates.[14] The text of each advertisement was studied to ensure all possible candidates were minimally qualified in terms of required experience. Positions also had to have been advertised in the previous *two* business days. This time-frame helps to ensure resumes are not submitted *after* the firm had received many suitable applications. This should maximize the chance of callback, providing greater statistical power. A randomly chosen fictitious resume and associated cover letter was then used to apply to each of the jobs the search returned.

[13] For example, all nurse cover letters suggested the candidate was kind, caring, and considerate. Software engineers were technically and analytically adept, and so on. These paragraphs drew from samples online for these types of positions. They did not vary meaningfully across individuals with the same career/degree and so any effects should be soaked up completely by the inclusion of field-level fixed effects.

[14] The author's limited resources ensures that data was collected at various times from May of 2015 up to as late as November of 2017. Dates were altered as needed to ensure each resume reflected a recent graduate with little work experience at the time of application.

In addition, to avoid bias, only open positions which asked for information explicitly available in the existing cover letter and resume were used. This resulted in many abandoned applications as job application systems often require more than a resume and cover letter to be submitted. Unfortunately, it is rarely clear what will be asked when beginning a job application. Applications often appear to request just a resume and cover letter be uploaded (or the information to be pasted into a firm-specific format) but upon clicking "submit" the system brings the applicant to another page of questions which can include basic personality tests or short essays specific to the firm, location, industry, or background of the potential applicant. To avoid the potential for bias from such essays and tests, these applications were abandoned at that point.

After applications were sent out, calls and emails requesting an interview were recorded. Similarly to Deming et al. (2016), a callback is considered any personalized contact.[15] While each resume reports a postal address the address is entirely fictitious (although it appears realistic) and any contact via postal mail would be missed. Bertrand and Mullainathan were concerned about this and contacted several human resources managers who suggested postal requests for interview were extremely rare. Given that Bertrand and Mullainathan's experiment was undertaken over 15 years ago the potential for bias introduced by requests for interview via postal mail can likely be ignored.

Data and Estimation Strategy

Estimation

As the assignment to an online degree is random, the estimate of δ from a regression of the following form can be viewed as the difference in callback probability between applicants who earn their degree online rather than at a traditional/in-person program:

$$y_{i,k} = \beta X_i + \delta D_i + \epsilon_i$$

[15] Paraphrasing slightly, employers who called and left a voicemail typically stated that they wanted to be called back to "discuss" an application. Sometimes employers who contacted an applicant were only seeking more information (such as additional documentation that they forgot to request via the job website) rather than expressing interest in interviewing. Because this information could not be provided without introducing bias, these applications were abandoned (the employers were contacted to state that the applicant was no longer interested). The estimates do not change appreciably by including or excluding these as callbacks.

In the estimation, $y_{i,k}$ takes on the value of 1 if firm k calls applicant i for interview. This binary outcome is predicted by fictional applicant-specific characteristics X_i and a dummy D_i to represent the result of the randomization. In this paper X_i includes GPA, years of experience, a measure of college selectivity (undergraduate selectivity as used by Dale and Krueger), gender, race (as indicated by name similarly to Bertrand and Mullainathan), and a binary indicator for the industry the applicant is in (business, engineering, nursing, and so on). The dummy D_i takes on the value of 1 if the randomization selects that individual as having a degree that was earned online.

A negative $\hat{\delta}$ would suggest the likelihood of getting a callback is reduced for online degree holders, even after accounting for other factors. Such an empirical approach would not be feasible using labor market survey data due to concerns about endogeneity and omitted variable bias. These concerns cannot be driving the results seen later in this paper as the randomization of D_i avoids that problem by construction.

The approach in this paper is subtly different to the matched-pairs approach of Bertrand and Mullainathan. However, it is similar to the Kroft et al. approach in the sense that they use unique resumes which are then assigned a randomized unemployment duration. For Kroft et al. four resumes are created for each MSA-job pair using simple rules for research assistants to follow. The actual contents of each resume are drawn from a pool of over 1,200 real resumes. They have research assistants record the objective facts of the generated resumes and note the duration of unemployment assigned. Then, the assistant moves on to the next MSA-job pair, creating another four unique resumes. Kroft et al. explicitly thank 14 research assistants. This labor intensive approach provides a bounty of data but is not feasible for a researcher with fewer available resources.

In contrast, the matched-pairs approach creates two (or more) versions of each resume and then examines the difference in callback rates as a function of the varied characteristic. Such an approach completely avoids concerns that results could be driven by systematic differences between the resumes which are separated into groups by randomization. For large enough samples true randomization ensures the estimated $\hat{\delta}$ would be the same but the empirical interpretation is different in a minor way. This paper's set up requires $\hat{\delta}$ to be interpreted as the difference in the mean callback rate between the group of people randomly assigned to have an online degree rather than a traditional degree. The approach leaves the possibility that differences between groups could drive the effects *if* the randomization fails.

Bertrand and Mullainathan's approach instead computes a pair predicted callback rates for each (fictional) individual: one for each value of the varied characteristic. Then, the estimated coefficient represents the average difference for all individuals. This is akin to doing a medical study on twins. In contrast, the results in this paper report the average difference between two groups of individuals who are assumed to be no different on average because of randomization. This is similar to a randomized trial with treatment and control groups who are not explicitly paired. With valid randomization, the assumption is that the differences between the group outcomes are only related to the treatment. The next section presents some summary statistics and examines how successful the randomization actually turned out to be.

Data

Estimates are based upon the outcomes of a total of 1,891 job applications completed for 100 different resumes. There were a total of 231 callbacks from the 1,891 applications completed, a callback rate of 12.2%. The overall callback rate is higher than other correspondence studies. For example, Kroft et al. have a callback rate of just 4.7%, while Bertrand and Mullainathan have a rate of 8.05%. Kroft et al.'s extremely low callback rate is likely because their resumes reflected applicants who were currently unemployed. The higher callback rate in this study is potentially due to design choices. For example, fictional applicants in this study are particularly well-matched to available positions, have a resume which reflects relevant experience, generally possess high GPAs, and include a sharp and succinct cover letter. In addition, openings applied to were less than 48 hours "old" in all cases. Resumes reflecting quality candidates should generate more callbacks and ensure adequate statistical power. In contrast, other resume studies examine callback rates in non-skilled labor markets but achieve power by applying for thousands of low-skilled positions, often sending several resumes to a single employer.

Table 1 first provides overall summary statistics on the (fictional) demographic characteristics of the resumes used to apply for positions. Then, the sample characteristics are stratified by degree assignment (online or traditional) to examine how the randomization actually fared. Despite the randomization, those who are assigned to have a traditional degree are slightly more likely to be male, have less work experience, and attended a less selective college (as measured using U.S. News undergraduate admission rates - higher numbers indicate less selectivity).[16] The table then shows the same summary statistics stratified by both race and gender. There are several clear differences in the demographic characteristics and callback rates of the various groups. For example, among the resumes which reflect a black name, the proportion of men in the sample is larger than in the other ethnic groups. These imbalances illustrate the importance of controlling for observable characteristics in later regression estimates.

Empirical Estimates

The collected data creates an unconventional panel data-set: there are repeated observations for each individual but no time component. Table 2 reports the paper's main empirical estimates. The estimates presented are from a probit regression with standard errors clustered by applicant.[17] The dependent variable is whether or not a callback was received (Callback=1 when a request for interview was received). The table reports a variety of specifications with controls added sequentially. The preferred specification in the final column includes controls for all covariates: race, sex, experience, college selectivity, career/field, and GPA.

The effect of an online degree is large and negative in all specifications. The coefficients presented are raw probit estimates and do not have straightforward economic interpretations. To aid intuition, the table reports post-estimation marginal effects. The marginal effects should be considered percentage point differences. That is, in the specification in column seven, the estimation reports that there is a 7.3 percentage point difference in callback rates between traditional and online degree holders, all else equal.[18] Given that the mean callback rate for online degree holders was 8.3 percent, a 7.3 percentage point difference suggests that a resume reflecting a traditional degree will receive almost twice as many callbacks for interview as a resume reporting an online degree, all else equal. As can be seen, the size of the estimate is consistent across specifications. To give these estimates some context, Bertrand and Mullainathan found whites were about 1.5 times

[16] See http://colleges.usnews.rankingsandreviews.com/best-colleges.

[17] Random effects estimates are presented in the Appendix. They differ only marginally from the pooled-sample estimates presented here. A fixed-effects specification is not feasible as, for each fictional resume, the independent variables do not change.

[18] There are several issues with computing marginal effects when the estimation involves a number of dummy variables. The main issue is that the procedure crudely considers the effect of the variable of interest at the average of variables that have no such interpretation. For example, the process sets the value of “gender” to its average value in the data.

more likely to receive a callback for interview as blacks, and Kroft et al. found that someone who is just one month unemployed is about 1.8 times more likely to receive a callback for interview than someone who has been unemployed for eight months.

The other variables in the regression tend to follow the stylized facts of the labor market. African and Latin Americans fare worse than Caucasians but in the preferred specification the callback rate for Black applicants was not statistically different to Caucasian applicants. Ethnicity is indicated only via name (see Section) and it is possible that the difference between Latin American names and the others is much clearer. As would be predicted, years of experience is associated with higher callback likelihood. Selectivity is measured using undergraduate acceptance rates from U.S. News and the negative coefficient implies attending a selective school matters. Higher GPAs are associated with higher callback rates but there is no statistical difference between male and female callback rates.

Table 3 re-estimates the final column of Table 2 by race and gender. Notice that the negative effect on callbacks is smaller for females and minorities relative to males and Caucasians. The estimated effect on minorities appears small but is still relatively large because the overall callback rate is lower for minorities regardless of type of degree conveyed to the employer (see Table 1). However, the disparity between male and female callback differences is striking. Upon further examination, there are two fictional female nurses in the sample who have two full years of experience and were randomly selected to have an online degree. Both have a call back rate of about 30% which is a higher callback rate than any other fictional candidate male or female, in any profession, regardless of degree program. Without those two well-qualified applicants, the disparity between callback rates would be larger both overall and for females, in particular. As Deming et al. (2016) note, nursing typically requires an occupational license which diminishes the role of academic qualifications in the screening process.[19]

The same issue drives the estimates in Table 4. In Table 4, the specification in the final column of Table 2 is estimated separately for business applicants (accountants and analysts), engineers (software and mechanical), and nurses. Because of the high callback rate for those two nurses with online degrees, nurses with online degrees appear to experience no difference in callbacks.

[19]Upon further examination, online nursing programs generally seem to also include a practical experience component. Only the coursework is completed 100% online.

These two applicants also happen to convey a Caucasian name which is driving the large negative coefficient for minority nurses.

Returns to Resume Characteristics

As mentioned in Section , a potential concern with audit studies is that findings are driven not only by the experimental variation but also by how the experimental resumes compare to their *subjective* competition. Take Bertrand and Mullainathan's finding that blacks receive fewer callbacks. If identical black and white resumes are interpreted differently, perhaps because employers have learned that one of the groups tends to oversell or fabricate their experience and skills more than another, then the effects Bertrand and Mullainathan find could just be an artifact of a labor market norm they (and perhaps employers, at least subconsciously) are unaware of. In that case, employers don't call blacks with a given resume quality but do call whites because they expect a black applicant to overstate their experience and abilities in order to *combat* expected discrimination. In that case, the signal of ability the employer takes from each resume is different not because the employer is discriminating but because of the actions of other applicants. This is something that a researcher cannot control. As Bertrand and Mullainathan find that employers respond only slightly more often to higher-quality resumes from black applicants, an "employer skepticism" explanation is a potential concern with their findings.

A similar concern arises in this paper. An employer may expect a person who has an online degree to report other compensating characteristics. When they do *not* see this, they infer something about the candidate's ability that the researcher is not controlling for. This problem is caused by attempting to hold all else equal when the changes made should *not* result in all else remaining equal. Empirically, these kinds of concerns should lead to different "returns" to aspects of resume quality for online degree holders, all else equal. Examining this requires a difference-in-difference estimation, illustrating how different years of work experience or a different GPA affects online and traditional degree holders differently. Table 5 reports estimates from the following type of difference-in-difference estimation;

$$y_{i,k} = \beta X_i + \lambda D_i + \gamma Characteristic_i + \delta D_i \times Characteristic_i + \epsilon_i$$

where *Characteristic* is a placeholder for sex, GPA, experience, and race, and all else is as described earlier. The coefficient of interest is now the interaction between having an online degree ($D_i = 1$) and $Characteristic_i$. A non-zero estimate for δ would suggest that there is a concern that the returns to the same characteristics across degree types are different.

The estimates from this exercise are presented in Table 5. Only the interaction terms are presented for the sake of space. The main effects are similar to the results in Table 2. The estimates suggest that experience does not appear to help online degree holders more than traditional degree holders. However, average years of experience in the sample is just 1.71. Over time, experience may be viewed as a better substitute for questionable academic qualifications. GPA has a statistically different return for online degree holders. The negative coefficient does not imply higher GPAs are worse, only that higher GPAs are not as helpful for online degree holders as they are for traditional degree holders. That is, if you earn an online degree, even a 4.0 GPA won't help that much. This is essentially a confirmation of the main takeaway of the paper: employers don't trust or value online education, at least not yet.

Estimates in columns five and six of Table 5 suggest that females with online degrees are called back more than men. However, the effect is not statistically different from zero.[20] Employers may be inferring that females may have valid reasons to do an online degree (children, two-body location problems, and so on). It also appears that having an online degree appeared to be less "harmful" to the prospects of African- and Latin-Americans than for Caucasians. The positive sign does not imply that callbacks are higher for those who do an online degree, only that the effect of an online degree is not as negative as it is for Caucasians (see Table 2). Employers may be inferring that the choice to pursue an online degree is made under different financial constraints for these students compared to Caucasian students. However, none of the race-degree interaction estimates presented are statistically different from zero.

Lastly, the same regression was estimated interacting college selectivity with having an online degree. The coefficient on the interaction term was essentially zero both in an absolute and statistical sense which suggests that the effect of an online degree does not vary as a function of the measure of selectivity chosen for this paper (undergraduate acceptance rates). That is, while those who attend a selective school fare better than those who do not (see Table 2) the relative

[20]Some of this effect is driven by the same two fictional female nurses discussed in the previous subsection.

negative effect of an online degree from such a school is neither more nor less pronounced than from any other school. This is perhaps a consequence of the mild variation in acceptance rates among the schools examined. Only schools which offer the same degree online and in person appear on resumes in this correspondence study, and these kind of schools are neither the most or least prestigious.[21]

Conclusion

This paper assumes that the move towards online education depends crucially upon associated labor market outcomes. For that reason, the paper tests how the labor market views degrees earned wholly online via a correspondence (or resume-audit) study. Empirical estimates strongly suggest that employers are skeptical of online degree programs. The difference in callbacks is the same or larger than the gap in callbacks found in similar studies on the effects of race and unemployment duration.

An important caveat is that some of the estimates presented in Section suggest that callback rates will be lower for those who pursue an online education *and* do not take any steps to counteract that decision. At the same time, this still implies employers are not yet ready to consider individuals with online degrees as being as attractive as those with traditional degrees.

The paper may be tackling a straw-man as it focuses on the effect of having a traditional four-year degree versus a degree earned online. If online education is pursued solely by those who would never earn a traditional degree, then the paper is redundant. However, given the growth of online education reported by Allen et al. (2016) the findings in this paper should interest students, professors, and administrators as the estimates confirm traditional modes of education are still viewed as superior to online education from an employer viewpoint.

An additional but somewhat moot caveat is that it is not clear what aspect of a traditional college education employers are responding favorably to. They may believe human capital formation is diminished in online programs relative to traditional degrees (even if it is not), they may believe the individual will be less socially adept, are inferring some socioeconomic characteristics, or they may feel a traditional college education gives students something more than just grades written

[21] In addition, the US News-reported undergraduate acceptance rate may not fully-capture the actual institutional prestige differences among these schools.

on a piece of paper. While understanding why students with online degrees fare poorly in the labor market is important, it is not the focus of this paper. The paper is agnostic about why and only cares about if labor market outcomes are affected by how a degree was earned. Until labor market outcomes are comparable, demand for traditional face-to-face learning from a professor in a classroom setting on existing college campuses can be expected to persist.

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A Exhibits

This section provides a sample resume (not used to complete job applications) and associated cover letter. The sample resume is formatted as an employer would see it.[22] For the cover letter, sometimes it could be attached as a file, sometimes it had to be copy and pasted. Dates mentioned in the cover letter were changed to be relevant to the date of application. No other changes were made across applications for a given resume. Resumes and cover letters for other applicants followed the same formula.

B Panel Effects

Typically, if there is reason to believe that differences *across* entities have an influence on the dependent variable then a random-effects model should be used rather than a pooled sample.[23] Upon estimating a random-effects model a Breusch-Pagan Lagrange Multiplier (LM) test can examine if treating the data as a panel is appropriate. In particular, the null hypothesis in the LM test is that variances across entities is zero. That is, there is no significant difference across units of observation: no "panel effect." For the data used in the paper, the results of an LM test suggest a panel approach may be preferable but the test statistic was only borderline significant. For completeness, Table B1 presents the same set of estimates as seen in Table 2 using a random-effects approach. Unsurprisingly, given the LM test was only borderline significant, the estimates convey very little new information compared to Table 2.

[22]The website used for applications automatically populates the resume with contact information used to sign up. That information must be redacted here. Sample responses from employers cannot be included for privacy and practical reasons: to render the job application website, voicemail and email provider, fictional applicant, and employer unidentifiable would involve redacting all of the information.

[23]Random-effects estimations assume that the error term is not correlated with independent variables to allow for values that are fixed for each individual to play a role as explanatory variables. Random effects specifications typically cause concerns about omitted variable bias but that is less of a concern here as there are no "missing" variables (by construction). Again, fixed-effects are not feasible due to zero variation in the independent variables.

Sample Applicant

Mechanical Engineer
Lexington, MA 02420
[redacted]@[redacted].com
(339) 970-[redacted]

BS degree in Mech. Engineering plus two years of hands-on experience.

Applications: SolidWorks, Visual Professional, AutoCAD, LabVIEW, and Microsoft Office.

Programming: C++, Python

Machining: ShopBot, Milling Machine, Lathe, Drill Press, shop tools and saws.

Work Experience

Mechanical Engineer
Sample Company A - Lexington, MA
July 2015 to Present

• Manage small and medium sized projects, from creating a work scope to completion and close out
• Using CAD create mechanical drawings, RFQs (request for quotes), inspect machined parts, and follow-ups
• Participation in completing reliability reports such as Risk Matrices, FTA (fault tree analysis), FMEAs (failure
modes and effect analysis), RBDs (reliability block diagrams), RCAs (root cause analysis)
• Resolved Root Cause Analyses on issues and failures, managed records for shared use by maintenance team
• Analyze machine performance by calculating MTBF (mean time between failure), MTTR (mean time to repair), and identify critical spare parts through frequency of failure
• Knowledge of reliability program to reduce risk, optimize cost, improve safety and quality in systems
• Implementing the Kaizen process, we have been able to increase OEE (overall equipment effectiveness) by various projects and focusing on large sources of downtime

Mechanical Engineer Internship
Sample Company B - Huntsville, AL
May 2014 to August 2014

• Shadowed aerospace engineering and computer science teams and helped prepare flight and advanced fabrication reports, debug MATLAB code, procure documents and spreadsheets of lab projects and results.

Education

Bachelor of Science in Mechanical Engineering (GPA 3.64)
Podunk State University (online) - Podunk, MA
September 2011 to May 2015

(**a**) Page 1

Skills

CNC (1 year), FABRICATION (1 year), LABVIEW (1 year), SOLIDWORKS (2 years), MATLAB (2 years), Microsoft Office (4 years)

Additional Information

Plays ultimate frisbee and enjoys soccer and basketball recreationally

Avid reader and founding member of local historical fiction book club

Volunteer for the Red Cross (spent 6 weeks volunteering as a construction worker for rural hospital in Kenya in 2013)

(**b**) Page 2

Figure A1: Resume for Sample Applicant

Sample Applicant
123 ABC St, Lexington, MA
(123) 456-7890, applicant@domain.com

March 25, 2017

Dear Sir/Madam:

Please accept this letter and accompanying resume as application for the advertised mechanical engineer position.

Since July of 2015 I have worked as a mechanical engineer at Sample Company A. I have developed a strong background in the methods and practices in mechanical system design, reliability testing, and troubleshooting failed mechanical equipment. In addition, my current role requires frequent use of Solid Works, AutoCAD, MATLAB, Microsoft Office, and more. I would enjoy the opportunity to improve my skills in a new position.

My Bachelor's degree in Mechanical Engineering, completed at Podunk State University, has given me a strong technical foundation. As part of my bachelor's degree I completed an internship with Sample Company B in Alabama. I have also volunteered as a construction worker in Kenya. This exposure to engineering work environments has been a tremendous benefit. These skills and experience along with strong communication, troubleshooting, and problem-solving skills will help me excel in a new role. In addition, my passion to learn new skills will make me an asset into the future.

A copy of my resume is enclosed for your review. I will be available for interview at a mutually convenient time to further discuss my capabilities and how I may be beneficial to your organization. I will be available to begin work at the end of April if you were to find me a good fit for this position. Please do not hesitate to contact me if you have any questions or need more information.

Sincerely,

____

Sample Applicant

Figure A2: Cover Letter for Sample Applicant

Table 1: Summary Statistics

All	Statistic	Raw Callback Proportion	Prop. Male	GPA	Selectivity	Years of Experience
Entire Sample	Mean	0.122	0.51	3.36	0.575	1.71
(N=100, n=1,891)	Std. Dev.	(0.33)		(0.50)	(0.20)	(0.77)

By Type of Education	Statistic	Raw Callback Proportion	Prop. Male	GPA	Selectivity	Years of Experience
Traditional Degree	Mean	0.159	0.53	3.38	0.583	1.69
(N=50, n=975)	St. Dev.	(0.37)		(0.33)	(0.20)	(0.76)
Online Degree	Mean	0.083	0.47	3.34	0.567	1.73
(N=50, n=916)	St. Dev.	(0.28)		(0.33)	(0.20)	(0.79)

By Race	Statistic	Raw Callback Proportion	Prop. Male	GPA	Selectivity	Years of Experience
Caucasian	Mean	0.138	0.48	3.45	0.58	1.56
(N=50, n=1,054)	St. Dev.	(0.34)		(0.22)	(0.20)	(0.66)
Black	Mean	0.09	0.64	3.20	0.537	1.72
(N=25, n=410)	St. Dev.	(0.29)		(0.40)	(0.20)	(0.87)
Hispanic	Mean	0.115	0.44	3.27	0.601	2.07
(N=25, n=427)	St. Dev.	(0.32)		(0.42)	(0.20)	(0.80)

By Gender	Statistic	Raw Callback Proportion	Prop. Male	GPA	Selectivity	Years of Experience
Male	Mean	0.121	1	3.39	0.577	1.77
(N=51, n=927)	St. Dev.	(0.26)		(0.33)	(0.20)	(0.78)
Female	Mean	0.122	0	3.33	0.573	1.65
(N=49, n=964)	St. Dev.	(0.37)		(0.327)	(0.20)	(0.76)

In the table"N" refers to the number of resumes/profiles. The small "n" refers to the number of applications completed using those N resumes. Selectivity is the only piece of information not provided by resumes. It is measured using U.S. News Undergraduate Admission Rates. Higher values indicate less selective institutions.

Table 2: Probit Callback Rate - Pooled-Probit Estimates - Full Sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Black		-0.216**	-0.334***	-0.239**	-0.226**	-0.0815	-0.0927
		(0.11)	(0.12)	(0.12)	(0.11)	(0.11)	(0.12)
Hispanic		-0.0846	-0.234	-0.297*	-0.334*	-0.318**	-0.313**
		(0.16)	(0.18)	(0.17)	(0.18)	(0.16)	(0.16)
Years of Experience			0.153***	0.146***	0.152***	0.180***	0.182***
			(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Selectivity (Undergraduate Acceptance Rate)					-0.0100***	-0.0108***	-0.0109***
					(0.00)	(0.00)	(0.00)
GPA						0.700***	0.704***
						(0.15)	(0.15)
Female							0.0609
							(0.10)
Online	-0.387***	-0.375***	-0.379***	-0.386***	-0.412***	-0.404***	-0.396***
	(0.12)	(0.12)	(0.12)	(0.11)	(0.10)	(0.10)	(0.10)
Observations	1,891	1,891	1,891	1,891	1,891	1,891	1,891
Marginal Effect (in Percentage Points)	7.6%	7.3%	7.3%	7.4%	7.7%	7.0%	7.3%
Race		Y	Y	Y	Y	Y	Y
Experience			Y	Y	Y	Y	Y
Career/Field Fixed Effect				Y	Y	Y	Y
College Selectivity					Y	Y	Y
GPA						Y	Y
Sex							Y

Standard errors clustered at the resume-level are in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The table reports the coefficients of interest from pooled-probit estimation with controls added sequentially. The coefficient estimates on career/field fixed effects are not reported to economize on space. Standard errors are clustered at the resume level. The marginal effects reported can be interpreted as percentage point differences in callback rates.

Table 3: Callback Rate - Pooled-Probit Estimates - By Subgroup

	(1) Females Only	(2) Males Only	(3) Caucasians Only	(4) Minorities Only
Black	-0.275	0.0353		
	(0.17)	(0.16)		
Hispanic	-0.430**	-0.177		
	(0.18)	(0.29)		
Experience	0.272***	0.0623	0.152**	0.171**
	(0.07)	(0.07)	(0.07)	(0.07)
Selectivity (Undergraduate Acceptance Rate)	-0.00785**	-0.0128**	-0.0165***	-0.00395
	(0.00)	(0.00)	(0.00)	(0.00)
GPA	0.680***	0.624***	0.703***	0.791***
	(0.24)	(0.23)	(0.27)	(0.17)
Female			0.0347	0.149
			(0.12)	(0.13)
Online	-0.257**	-0.519***	-0.567***	-0.187
	(0.13)	(0.15)	(0.13)	(0.14)
Observations	927	964	1,054	837
Marginal Effect (in Percentage Points)	4.8%	9.4%	9.8%	3.2%

Standard errors clustered at the resume-level are in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The coefficient estimates on career/field fixed effects are not reported to economize on space. Standard errors are clustered at the resume level. The marginal effects reported can be interpreted as percentage point differences in callback rates.

Table 4: Callback Rate - Pooled-Probit Estimates - By Field/Profession

	(1) Business	(2) Nursing	(3) Engineering
Experience	0.110	0.347***	0.131**
	(0.09)	(0.10)	(0.06)
Black	0.180	-0.726**	-0.135
	(0.22)	(0.34)	(0.14)
Hispanic	-0.283	-0.629***	0.601***
	(0.24)	(0.23)	(0.22)
Selectivity	-0.0146***	0.00111	-0.00527**
	(0.00)	(0.01)	(0.00)
GPA	0.679**	0.984***	0.469**
	(0.29)	(0.22)	(0.20)
Female	0.0865	-0.095	0.110
	(0.20)	(0.11)	(0.12)
Online	-0.474**	-0.00609	-0.435***
	(0.20)	(0.17)	(0.12)
Observations	849	457	585
Marginal Effect (in Percentage Points)	7.8%	0.2%	7.6%

Standard errors clustered at the resume-level are in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The coefficient estimates on career/field fixed effects are not reported to economize on space. Standard errors are clustered at the resume level. The marginal effects reported can be interpreted as percentage point differences in callback rates.

Table 5: Probit Callback Rate - Pooled-Probit Estimates - Returns to Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Experience × Online	-0.0254	0.0982						
	(0.09)	(0.10)						
GPA × Online			-0.425	-0.710**				
			(0.29)	(0.28)				
Female × Online					0.355	0.215		
					(0.23)	(0.21)		
Black × Online							0.198	0.153
							(0.22)	(0.21)
Hispanic × Online							0.362	0.416
							(0.31)	(0.29)
Observations	1,891	1,891	1,891	1,891	1,891	1,891	1,891	1,891
No. of Resumes	100	100	100	100	100	100	100	100
Experience	Y	Y		Y		Y		Y
Career/Field Fixed Effect		Y		Y		Y		Y
College Selectivity		Y		Y		Y		Y
GPA		Y	Y	Y		Y		Y
Sex		Y		Y	Y	Y		Y
Race		Y		Y		Y	Y	Y

Standard errors in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The table reports coefficients of interest from random-effects probit estimations. As most interaction coefficient estimates are not significantly different from zero, marginal effects are not reported here.

Table B1: Probit Callback Rate - Random Effects Estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Black		-0.180	-0.322**	-0.234	-0.226	-0.0850	-0.101
		(0.15)	(0.16)	(0.16)	(0.15)	(0.14)	(0.12)
Hispanic		-0.111	-0.303*	-0.367**	-0.383**	-0.335**	-0.330**
		(0.15)	(0.16)	(0.16)	(0.15)	(0.14)	(0.16)
Experience			0.182***	0.177***	0.180***	0.193***	0.195***
			(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Selectivity					-0.0107***	-0.0110***	-0.0111***
				(0.00)	(0.00)	(0.00)	
GPA						0.689***	0.697***
						(0.17)	(0.15)
Female							0.0884
							(0.10)
Online	-0.357***	-0.338***	-0.342***	-0.350***	-0.375***	-0.364***	-0.354***
	(0.12)	(0.12)	(0.12)	(0.11)	(0.11)	(0.10)	(0.10)
Observations	1,891	1,891	1,891	1,891	1,891	1,891	1,891
No. of Resumes	100	100	100	100	100	100	100
Marginal Effect (in Percentage Points)	7.2%	6.9%	7.3%	7.5%	7.6%	7.4%	7.2%
Race		Y	Y	Y	Y	Y	Y
Experience			Y	Y	Y	Y	Y
Career/Field Fixed Effect				Y	Y	Y	Y
College Selectivity					Y	Y	Y
GPA						Y	Y
Sex							Y

Standard errors clustered at the resume-level are in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The table reports the coefficients of interest from random-effects probit estimations with controls added sequentially. The marginal effects reported can be interpreted as percentage point differences in callback rates.