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IZA DP No. 12960

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ABSTRACT

The Demand for Interns*

We describe the demand for interns in the U.S. using ads from an internship-specific website. We find that internships are more likely to be paid when more closely associated with a specific occupation, when the local labor market has lower unemployment, and when the local and federal minimum wage are the same. A résumé audit study with more than 11,500 applications reveals that employers are more likely to respond positively when internship applicants have previous internship experience. Employers are also less likely to respond to applicants with black-sounding names and when the applicant is more distant from the firm.

JEL Classification: J23, I23

Keywords: internships, training, audit study

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Most college students in the United States obtain their first relevant job experience as interns. Although questions regarding internships are virtually absent from nationally representative surveys, the existing evidence suggests that more than 60 percent of recent college graduates in the United States held an internship at some point during their college career (NACE 2018), doubling the incidence from the 1980s (Lindquist and Endicott 1992). Employers claim that internships at their firm or in their industry are the most influential characteristic that students can have to land a job (NACE 2017), and their increasing prevalence may reflect a response by students to the prioritization of relevant experience in hiring decisions (Finch, et al. 2013; Cappelli 2015; Nunley, et al. 2016; Nunley, et al. 2017). Internships may also be a both symptom and cause of growing underemployment of new college graduates (Abel, Deitz, and Su 2014).

Despite the perception of their increased importance, there is limited actual evidence regarding the impact of internships on labor market outcomes. Observational and non-representative studies (Knouse, Tanner, and Harris 1999; Gault, Redington, and Schlager 2000) find a positive correlation between holding an internship and students' subsequent employment outcomes. Using a resumé audit study, Nunley, et al. (2016) provide perhaps the best causal evidence that internships substantially increase the offer of interviews in the U.S. by about 13 percent (more than 2 percentage points, on a base interview rate of about 17 percent). In Germany, Margaryan, Saniter, Schumann, and Siedler (2019) exploit variation in the incidence of internship holding induced by changing university requirements and find that having done an internship raises earnings over the life cycle in Germany by about 6 percent. Except for these few studies, there is little beyond anecdote that suggests a strong link between having held an internship during one's university career and later labor market success.

If little is known about the effect of internships on the job prospects of new college graduates, even less is known about the market for interns itself. This paper fills that void and is the first to describe the demand for interns as well as the first to assess what leads to success in the internship market. We first employ data from a prominent online internship website to describe the demand for interns and examine the correlates of paid internships. We apply a machine learning algorithm developed for the U.S. Department of Labor to the text and titles of 28,551 internship ads and assign detailed occupations to them. We find that, conditional on other characteristics, internships that are close matches to particular occupations are more likely to be paid and full time, i.e. more "job-like." A strong negative relationship between the local unemployment rate for young workers and the incidence of paid interns, suggests a connection between the "regular" labor market and the market for interns. We also find evidence that above-federal minimum wages reduce the incidence of paid internship advertisements.

To assess how candidates' and internship characteristics affect internship success, we conduct the first and only large-scale résumé audit of the market for interns. Race-associated names, college major, GPA, and previous internship and work experience were randomly assigned to 576 distinct profiles, which were then submitted to more than 11,000 positions advertised on a popular website devoted exclusively to internships.

We find, not surprisingly, that firms are more likely to respond to applicants for unpaid internships than for paid internships. Firms also respond less frequently to applicants for internships in high-paying occupations. The résumés that were randomly assigned black-associated names were substantially less likely to receive a positive response from firms, and applicants who were more distant from the firm were less likely to receive a positive response.

Using the same machine learning algorithm as in the descriptive analysis, we estimate that internships that are more closely matched to an occupation yield fewer positive responses from firms, *ceteris paribus.* Most importantly, perhaps, we find that a strong determinant of success in landing an internship is having previously held an internship. Unlike "usual" college jobs (like lifeguarding or working in retail), which have little or no effect, prior internships raise the probability of a positive response for a subsequent internship by about 30 percent (2 percentage points on an unconditional response rate of 6 percent). This suggests that landing a first internship may be a key determinant of future success in both the internship and labor markets.

I. What is an Internship?

The fundamental characteristic of internships is their fixed duration, usually less than one year, and often much shorter.[1] Such short durations, with low search and separation costs, may afford an efficient opportunity to see whether a student and firm are a good match for one another (Jovanovic 1979), and firms likely hire interns in part as a screening device for subsequent regular employment. A 2015 survey of a non-representative sample of U.S. firms indicates that 90 percent of interns who return for a second internship were offered full-time employment, and almost 90 percent of those offered full-time employment accepted the offers (NACE 2015). In addition to offering an opportunity to observe their "fit" with a particular employer, students may take an

[1] Apprenticeships, while relatively uncommon in the U.S., share some characteristics with internships – particularly their fixed length and lack of formal pay. They generally target the lower-skilled portion of the labor market (see, for example, Fersterer, Pischke, and Winter-Ebmer 2008), however, and even in German-speaking countries where they are more common, internships are prevalent for college-aged and college-educated individuals (Margaryan, Saniter, Schumann, & Siedler, 2019).

internship to gain employment experience or to signal their interest in a specific industry. Regardless of whether such experience also conveys transferrable human capital, students may perceive that holding an internship will send a positive signal in the market for regular jobs and enhance their ability to land a position in the regular job market.

Unlike regular jobs, some internships are unpaid. Following a recent decision of the U.S. Second Circuit Court of Appeals, the current legal standard determining an intern must be paid or not hinges on who is the "primary beneficiary" of the internship (Harvard Law Review 2016). This interpretation, which would decide the legality of an unpaid internship on a case-by-case basis is somewhat at odds with those given by the Fair Labor Standards Act (FLSA). Under the FLSA, the U.S. Department of Labor does not consider an intern an "employee," and therefore entitled to be paid, if the internship is similar to training obtained in an educational environment and the intern is not entitled to pay or regular employment with the firm in the future.[2] Enforcement of these guidelines is far from universal, however. Firms presumably have some latitude in whether they offer paid or unpaid internship opportunities. If interns produce positive value for firms (either by reducing search costs or by producing output), the incidence of paid internships may vary by the kinds of skills demanded by the internship and the state of the local (paid) labor market.

[2] See U.S. Department of Labor Fact Sheet Number 71 (https://www.dol.gov/whd/regs/compliance/whdfs71.htm, last seen 1 April 2019) for the full set of legal tests that have been applied to determine whether the firm or the intern is the "primary beneficiary" of the relationship.

II. Demand for Interns: Internship Ads

We use internship ads posted to a popular online internship website both to describe the internship market as well as the basis for our résumé audit study.[3] Each ad contains a title, a description of the position, the requirements for the position, whether the internship is paid or unpaid, whether the internship is full- or part-time, the date the ad was posted, and the name and location (usually the full address) of the firm positing the ad.[4] We use the address of the firm to determine its latitude and longitude and to assign it to a core-based statistical area (CBSA).[5]

The internship-specific site that we use has two advantages over more general job sites. Although internships are often listed on Internet portals also used for "regular" jobs, the particular site we use requires that the ad indicate whether the internship is part- or full-time and whether the internship is unpaid or paid. This is not the case on other portals. In addition, all communication between applicants and firms takes place on the website itself. In contrast to audit studies like Jaeger, Nunley, and Seals (2020) in which correspondence takes place via email and firms' responses can also be made via telephone, having all interactions with firms take place only on the portal greatly facilitates applying for positions and observing firm responses.

We use the text from the title, description, and requirements for each ad as inputs to a machine learning algorithm, the O*NET-SOC Autocoder, that assigns an 8-digit Standard

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[3] Our IRB agreement prevents us from revealing which Internet site we used.

[4] The posting date was not available when we did the audit study but is available in the descriptive data we gathered later.

[5] Geocoding is done using the OpenCage geocoder API (http://www.opencagedata.com, last seen 14 March 2019). We use CBSAs in the analysis rather than Commuting Zones because we want to measure unemployment rates at monthly rather than annual frequency.

Occupational Classification (SOC) to the ad. The O*NET-SOC Autocoder was developed by the U.S. Department of Labor and then enhanced by R.M. Wilson Consulting as a standard means of assigning an SOC to job ads.[6] The algorithm also assigns an occupation-match score that represents how closely an ad matches the characteristics of a given detailed occupation category. Higher match scores represent more specific occupational matches, and scores higher than 60 are considered acceptable matches. Figure 1 displays the kernel density estimate for the occupation-match score, indicating substantial variation in the extent which the ad text matches the characteristics of the detailed occupation to which it is assigned.

By using an Internet site for our analysis, we should note that we do miss internships that are advertised only on university campuses or privately (i.e. through the "old boy network"). It is difficult to assess how much of a concern this is for the external validity of our study, since there are no publicly-available datasets that provide information on the number of internships at any one time. The Conference Board Help Wanted Online index does include internships, but they are not separately reported.[7] Burning Glass (http://www.burning-glass.com) also collects information on internships in its broad web-scraping measures of the labor market. Both sources would also suffer, however, from the lack of "local" internship ads on campuses or the existence of private internship search activities by firms. By focusing on a single internet site, however, we eliminate

[6] The O*NET-SOC AutoCoder was designed specifically to classify job ads into occupations. The training dataset for the algorithm is the O*NET database of job characteristics. Details on the Autocoder can be found on the FAQ tab at http://www.onetsocautocoder.com/plus/onetmatch (last seen 1 October 2019), which provides information on the uses, accuracy, and methodology of the Autocoder. R.M. Wilson Consulting, Inc. owns the rights to the O*NET-SOC Autocoder and provides access to it for fees that vary based on the number of records processed. Javed et al. (2015) note that CareerBuilder, a large online job board, used the same algorithm to label job advertisements used in the classification of job titles for the creation of a large training data set for Carotene, their proprietary algorithm.

[7] Personal email from Jeanne Shu, Associate Director of the Help Wanted Index Online, 1 February 2017.

problems associated with counting the same internship multiple times because it appears on multiple job sites.

III. Describing the Demand for Interns

To describe the demand for internships, we web-scraped all of the internship ads posted to the site used in our study on two days, one in November 2016 and one in March 2017. About 44 percent of ads were present on the website on both dates. The vast majority of the ads were posted in 2015 (34.8 %) and 2016 (56.2%), with 7.3% posted in the first quarter of 2017, with the small remainder posted prior to 2015. The average length of time from posting until we observe an ad was 9 1/2 months. Of the ads we observed in November 2016, 45 percent had been removed four months later in March 2017. Non-repeat ads (i.e. those that did not appear in November 2016) comprise about 10 percent of the ads in March 2017. There is therefore a fair bit of stability in firms' demand for interns over time. For our subsequent analyses, we drop one of each of the repeat ads (8,266 ads in total), ads with a posting date prior to 2014 (4 ads) as well as those where the geographic information is not sufficient to permit us to match the ad to a CBSA. We also dropped 61 ads from firms in Alaska or Hawaii. Our final data set includes 28,551 ads.[8]

Figure 2 shows the geographic distribution of internships across CBSAs per 100,000 individuals aged 18 to 25.[9] There is substantial variation in the availability of internships across

[8] The details associated with the sample construction, data sources, and other pertinent information about the data are provided in the Data Appendix.
[9] We average the number of internships from the two points in time, November 2016 and March 2017, and plot that number relative to the average number of individuals aged 18-25.

the U.S., with the greatest density in large metropolitan areas along the coasts and upper Midwest. The geographic distribution of paid internships is also different from that for unpaid internships. Figure 3 shows the geographic distribution of the average share of paid internships across the two periods. While the number of internships per capita is higher on the coasts, paid internships are less common along there than in the central part of the U.S.

Table 1 shows the cross-tabulation of part-time/full-time status and paid/unpaid status. About 72 percent of internships are part-time and about 62 percent are unpaid, with more than half being part-time and unpaid. There is a strong relationship between full-time internships and paid status, with 71 percent of full-time internships being paid. The opposite is true for part-time internships, where 74 percent are unpaid. The χ^2 statistic for the test of independence of part-time/full-time and unpaid/paid status is approximately 5,000, which indicates that independence is clearly rejected.

We show the distribution of major (2-digit) occupations assigned by the O*NET-SOC Autocoder from the text of the ads in Table 2. While most major occupation categories are represented, two-thirds are concentrated in just three occupation groups: Arts, Design, Entertainment, Sports and Media (31.4 percent), Business and Financial Operations (21.7 percent), and Sales and Related (14.2 percent). Despite this concentration, 357 unique detailed occupation (6-digit SOC) groups are represented in our data.

Columns 2 and 3 in Table 2 show the percentage of each 2-digit occupation group that are paid and part-time, respectively. There is substantial variation in the paid incidence across the three most prevalent occupation groups, ranging from 23.3 percent of Arts and Design internships to 36.7 percent of Business and Financial and 72.4 percent of Sales internships. Consistent with the overall relationship between paid and full-time internships from Table 1, the correlation between the percentage paid and percentage part-time across occupations is -0.81. The majority of internships are unpaid and part time, but there are three major occupation groups (architecture and engineering, sales, and construction and extraction) in which more than half of the internships are paid, however, and only one major occupation group (sales) in which more than half of internships are full time.

We assign skill requirements to each internship by matching the 6-digit SOC codes, produced by the Autocoder algorithm, with information in the O*NET 21.1 (released in November 2016). Using the data from O*NET, we create three variables that measure social skill task intensity, repetitive or routine task intensity, and nonroutine-analytical task intensity (details can be found in the Data Appendix). Following Autor, Levy, and Murname (2003) and Deming (2017), these variables are weighted percentile ranks, measured on a 0-10 scale.

The firm address information in each ad allows us to assign each internship to a local labor market (CBSA). This permits us to match the local unemployment rate in the month in which the ad was posted from the Local Area Unemployment Statistics provided by the Bureau of Labor Statistics[10] as well as the minimum wage that was in effect at the time.[11] Using the geographic location of the firm, we are also able to calculate the total enrollment in higher education

[10] The Local Area Unemployment Statistics are available at the following link: https://www.bls.gov/lau/home.htm (last seen 19 October 2019).

[11] Two data sources are used in order to determine the prevailing minimum wage in the firm's location by culling information from two sources: Vaghul and Zipperer (2016) (https://equitablegrowth.org/working-papers/historical-state-and-sub-state-minimum-wage-data/, last seen 19 October 2019) and the Inventory of US City and County Minimum Wage Ordinances from UC Berkeley's Labor Center (http://laborcenter.berkeley.edu/minimum-wage-living-wage-resources/inventory-of-us-city-and-county-minimum-wage-ordinances/, last seen 19 October 2019).

institutions within a 100 mile radius using data from the College Scorecard in 2016-2017.[12] Because unpaid internships often carry college credit, one would expect that they would be more prevalent in areas with more university students.

IV. Determinants of Paid Status and Internships' Connection to the Regular Labor Market

We argued above that internships likely serve two purposes for the firm. First, internships allow the firm to screen workers' productivity at lower costs than hiring and then firing new regular employees. Second, interns may actually produce value.[13] The overall demand for interns is therefore likely to fluctuate with the state of the local economy. Firms' need to screen workers will be lower when overall demand for labor is slack, as will firms' demand for the output that interns produce. Because paid internships are closer to regular jobs than unpaid internships, demand for paid interns is likely to be more sensitive to local labor market conditions than the demand for unpaid interns. We would therefore expect the incidence of paid internships to decrease with increases in the unemployment rate and increases in the minimum wage. Through the Fair Labor Standards Act, paid internships are subject to minimum wage and overtime laws while unpaid internships are exempt.

Between 2012 and 2017, when the ads we use were first posted online, the U.S. economy was

[12] College Scorecard data can be downloaded from https://collegescorecard.ed.gov/data/ (last see 16 August 2019).

[13] As noted above, recent interpretations of the Fair Labor Standards Act have stated that unpaid interns must be the "primary beneficiary" of their internship, that its main goal should providing education or training, and that there can be no expectation of further employment with the firm. A strict interpretation, in which firms only incur costs for unpaid interns, but derive no benefits, would seem at odds with the existence of unpaid internships at all. It seems reasonable to expect, however, that paid internships are far more sensitive than unpaid internships to state of the local labor market.

generally improving and the unemployment rate decreased in the majority of labor markets over this period, but the extent of improvements in labor market conditions varied both within and between CBSAs. At the same time, some states and localities passed laws requiring increases in the wage floor. Similar to the unemployment rates, these changes produce variation within and between CBSAs.

Figure 4 shows the incidence of paid internships in each CBSA from our web-scrapes plotted against the average unemployment rate across 2015 and 2016 (when 90 percent of the ads were posted). A one-percentage-point increase in the unemployment rate is associated with a 4.7 percentage point, statistically significant decrease in the incidence of paid internships in the CBSA. Increases in the minimum wages could result in fewer paid internships, as firms find it less advantageous to pay interns as the wage floor increases. Similarly, in Figure 5, we plot the incidence of paid internships against the prevailing minimum wage. The incidence of paid internships decreases by 4.6 percentage points for each $1 increase in the minimum wage. Figures 4 and 5 point to a strong link between paid internships and the state of the local labor market.

We assess how characteristics of internships and the labor markets in which they appear affect whether an internship is paid with the following regression:

$$
\begin{aligned}
paid_{j,o,c,l,d} &= \beta_0 + \beta_1 x_j + \beta_2 z_o + \varphi_{\tilde{o}} + \varphi_l + \beta_3 score_{j,o} \\
&\quad + \beta_5 minwage_{c,d} + \beta_6 unemp_{l,d} + \varepsilon_{j,o,c,l,d}.
\end{aligned}
\tag{1}
$$

The subscripts *j*, *o*, *c, l*, and *d* index ads, occupations, cities, CBSAs, and the month-year the ad was posted online, respectively. The variable $paid_{j,o,c,l,d}$ equals one when an internship is paid and zero otherwise; x_j is a vector of ad-specific explanatory variables, including an indicator variable for part-time status, the natural log of the number of students enrolled in a four-year college within 100 miles of the firm searching for an intern, an indicator variable for ads retrieved in the fall, and an indicator variable for whether the same ad was extracted in both the fall and spring data; z_o is a vector of the task content variables (social skills, routine tasks, and analytical tasks) measured at the occupation level; $\varphi_{\tilde{o}}$ represents major occupation group fixed effects at the 2-digit level;[14] φ_l represents CBSA fixed effects; $score_{j,o}$ represents two indicator variables, one indicating occupation-match scores between 60 and 90 and the other indicating occupation-match scores of 90 and above; $minwage_{c,d}$ is the prevailing hourly minimum wage in the firm's location at the posting date of the ad; $unemp_{l,d}$ is the unemployment rate for the CBSA in which the advertising firm is located during the posting month of the ad; and $\varepsilon_{j,o,c,l,d}$ represents factors not accounted for in equation (1).[15] The β_k are the parameters of primary interest. We compute cluster-robust standard errors with two-way clustering on CBSAs and detailed occupation groups, given the non-nested nature of occupations and CBSAs (Cameron, Gelbach and Miller 2011).

We present the estimated effects of the variables in equation (1) in Table 3. The first four columns present results for all internships. In column 1, we do not control for any fixed effects, while in column 2 we control for 2-digit occupation fixed effects. Column 3 adds CBSA fixed effects to the specification from column 2. In column 4, we substitute occupation fixed effects at

[14] It is not possible to hold constant detailed occupation fixed effects when z_o is included in equation (1), as the variables would be perfectly collinear. However, we check the sensitivity of the other estimates to the inclusion of 6-digit SOC fixed effects.

[15] Because the minimum wage is tied to the city in which the firm is located, we substitute φ_c for φ_l as a robustness check, and swapping these different geographic fixed effects has no meaningful impact on our estimates.

the 6-digit level for those at the 2-digit level. As we discuss below, the results are generally consistent across specifications.

As we would expect from the results in Table 1, there is a strong negative relationship between paid status and part-time status. Part-time internships are between 32 and 39 percentage points less likely to be paid, depending on the specification. These effects are extremely large relative to the unconditional incidence of paid internships of 39.3 percent.

Of the three skill intensity measures, we find a statistically and economically significant relationship between paid status and non-routine cognitive tasks. Each additional point, on the 10-point intensity scale, increases the probability that an internship is paid by about 2 percent points, once we control for labor market fixed effects in column 2. The estimated coefficients on social skill and routine task intensities are small and not statistically different from zero. Because the skill variables are assigned at the 6-digit level, all three of the skill variables fall out of the model in column 4.

As in Figure 5, we find a generally monotonic and highly statistically significant relationship between the occupational specificity of the ad, as measured by the Autocoder match score, and the probability that an internship is paid, even when controlling for 6-digit occupation codes in column 4.[16] We interpret this result as indicating that the more "job like" an internship is (i.e. the more the firm is seeking to fill a specific occupational role), the more likely is the internship to be paid. This interpretation is also supported by the results for the effect of the unemployment rate at the time the ad was posted and the prevailing local minimum wage.

[16] The occupation-match score is not related to the number of words in an ad. The results in Table 4 are also robust to the inclusion of the number of words in each ad. Both results are available from the authors by request.

Consistent with the unconditional results in Figures 4 and 5, both variables have a negative and statistically significant relationship with paid status, indicating that local labor market conditions have an impact on whether a firm advertises for a paid internship. A one percentage point increase in the unemployment rate is associated with an approximately 3 percentage point reduction in the share of paid internships, and a $1 increase in the minimum wage in the local labor market is associated with a slightly less than 2 percentage point reduction in the incidence of paid internships. Overall, there is a strong link between the local labor market for young and low-wage workers and paid status. Along with the results for the occupation match score, these results also suggest that the demand for paid interns behaves in ways that are very much like what one would expect for regular jobs.

The size of the estimated relationship between college enrollment and paid status is negative, as expected, and statistically significant in columns 1 and 2, but because there is relatively little variation in this variable within CBSAs, the effect disappears when CBSA fixed effects are included in columns 3 and 4.

We present results for part-time internships alone in column 5 and full-time internships alone in column 6 using the specification that includes 2-digit occupation and CBSA fixed effects. The relationships between paid incidence and the skill intensity variables is similar to those for all internships. We find, however, the variables related to the regular labor market (occupational match score, unemployment rate, and the minimum wage) are less strongly associated with paid internships for part-time internships than for full-time internships. This is consistent with the notion that full-time paid internships are much more like jobs than part-time unpaid internships.

V. Who Gets an Internship? Experimental Evidence

As we have noted, there is little empirical evidence on how internships affect labor market success. There is even less evidence regarding success in the market for internships itself. To gauge what characteristics of applicants and internships affect the probability of success (measured by positive firm responses), we conducted a resumé audit study of the internship market. To our knowledge, this is the only audit study of the market for interns in the U.S.

A. Experimental Design

Following the design of previous audit studies, we submitted fictitious résumés to internship openings during the fall and spring semesters of the 2015-2016 academic year via the widely-used online internship website discussed earlier.[17] Although most audit studies submit resumés in response to job ads, we created online profiles for the fictive applicants.[18] Each profile was then used to apply to 10 different internships and, as a result, the experiment has a clustered design. To be consistent with the literature, however, we will use "résumé" and "profile" interchangeably.

We created 576 profiles in each semester, with each profile forming a unique cluster along three dimensions: applicant name, major field of study, and university. We used two distinctively

[17] As noted above, we are prohibited by our IRBs from revealing the identity of the website used.

[18] Two recent audits of the real-estate rental market use online profiles of fictitious, prospective renters with ethnic-sounding names (Gaddis and Ghoshal 2015; Edelman, Luca and Svirsky 2015).

white names (Wyatt Schmidt and Colin Johannson) and two distinctively black names (Darius Jackson and Xavier Washington).[19] Profiles for each racially-distinct name were assigned six major fields of study (Biology, Economics, Business Administration, Marketing, Psychology, and English) at twenty-four, large, public universities that span the U.S., yielding 24 profiles at each of the 24 universities, or 576 profiles in total, in each semester.[20] Our data includes 1,152 clusters because each name-major-university cluster is assigned a different randomly-generated résumé in the fall and spring semesters.[21] Each résumé included an email (direct message) address, specific to the platform, to which prospective firms could respond.

We used the program created by Lahey and Beasley (2009) to randomize other attributes included in the profiles, including grade point average (GPA), work experience while in college, past internship experience, volunteer experience, and computer skills. The combination of the name-major-university clusters and the random assignment of the résumé attributes ensures that so-called template bias is avoided (Lahey and Beasely 2009). Table 4 presents summary statistics for the résumé attributes for all internships (column 1), unpaid internships (column 2), paid internships (column 3), part-time internships (column 4), and full-time internships (column 5).

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[19] In response to the critique provided in Charles and Guryuan (2011), it is important to select names that are common in the populations of both white and black babies. Because our fictive applicants would tend to be in their early-20s when apply for the internships, we use the Social Security Name Database, which provides rankings on the popularity of particular first names (overall, not by race), to ensure the names chosen are indeed common in the population. Xavier and Darius are ranked 139 and 155, and Wyatt and Colin are ranked 124 and 197. These rankings indicate that the names chosen for our experiment were given to babies at similar rates. The names, however, should signal race. The racial signal of the first names is enhanced when combined with racially-distinct surnames, which are selected based on data from the 2000 Census. We contend the first and surnames assigned to the fictive applicants are unlikely to be perceived as "odd" by employers.

[20] Our IRBs prohibit us from revealing the names of any firms or universities used in the experiment.

[21] Assuming a cluster size of 10, our initial power calculations for a randomized control trial with a clustered design indicate that for a detectable difference of one-percentage point with 80 percent power, we would need 47 clusters per arm (94 clusters total).

Resumé attributes are balanced across the different types of internships to which applications were submitted.

To produce a random sample to which we could submit the fictive résumés, we followed a five-step process. The process follows the menu choices on the website employed to generate a list of internship ads from which one ad was randomly chosen.

1. *Randomly select one of three "target" labor markets that were likely to be where students from the university on the résumé would apply.*

   For each of the 24 universities that were included in the design, we identified three target labor markets which were the most likely to be where students would apply. If, at any time in the subsequent process, there were no positions that met the relevant criteria in steps 2 through 6, research assistants were instructed to select another metropolitan area that was a similar distance from the university as the initial metropolitan area.

2. *Randomly select one of three internship categories from marketing, research, or business.*

   We chose these categories because they included large numbers of both paid and unpaid internships as well as part- and full-time internships consistently across cities.

3. *Randomly select part-time or full-time internship.*

4. *Randomly select paid or unpaid internship*.

5. *Randomly select the webpage from which the internship is to be chosen.*

   After completing steps 2-4, there are multiple numbered pages of internships available when the internship advertisements are displayed. Rather than select internships on the first page, we generate a random number that determines from which page the internship should be chosen.

6. *Randomly select the internship on the webpage to which a résumé would be submitted.*

   After step 5 is completed, the site displays 10 internship advertisements and one of these ads is chosen randomly. It is to this ad to which a résumé will be submitted.

We submitted 11,520 résumés in total, with 5,760 résumés submitted in each the spring and fall semesters of the 2015-2016 academic year.

After submitting a résumé to a particular internship position, we monitored the profile accounts for responses from employers. We classified these responses into three types: expressions of interest, interview requests, and location inquiries. In an effort to streamline the main findings from the experiment, we create an outcome variable that combines both expressions of interest and interview requests into one variable. We refer to this outcome either as a "callback" or "positive response", which is the primary outcome variable in the analysis of employer responses. Our results are qualitatively similar if we use either expression of interest or interview requests separately as the outcome measure.

We present rates of different types of employer responses in Table 5. Overall, employers responded in a positive way (either requesting more information or an interview) approximately 6 percent of the time, which is in line with other recent audit studies of the conventional labor market (e.g., Lahey 2008). Unpaid internships, not surprisingly, have a positive response rate (about 8 percent) that is twice as large as that for paid internships (about 4 percent). Interview request rates are relatively even more likely for unpaid internships (4.3 percent) than for paid internships (1.8 percent). There is no obvious pattern for the relationship between part-time and full-time internship positive response rates – both are around 6 percent.

B. Incorporating External Data Sources

As with the analysis of internship ads, we input the text of each ad to which we submitted a résumé into the SOC Autocoder to classify each internship into a detailed occupation category. This allows us to examine how different skill requirements affect the probability of firm responses.

As above, we include the unemployment rate in the CBSA of the firm at the time when the résumé was submitted, as well as the college enrollment within 100 miles of the firm in 2016-17 in the analysis.[22]

C. *Locations and Occupations*

The occupational distribution of the ads to which we applied is representative of those for young, college-aged workers at the time of our audit. Using data from the American Community Survey, we find that the seven major occupations that comprise over 90 percent of our web-scraped sample employ about 70 percent of young workers with college degrees. In addition, the majors assigned to the fictive applicants are common among workers employed in the occupations that correspond to the ads to which we submit résumés. Lastly, we compare the occupational distribution of the ads to which we applied to the internship classification presented by Burning Glass, we find extensive overlap between our data and the Burning Glass data.[23] We are confident that the ads to which we applied are representative of the general internship and labor markets facing college-age students and recent college graduates, and our results should therefore be generally externally valid.

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[22] The Data Appendix provides more information on the incorporation of external data sources, including observations lost due to an inability assign a SOC code or merge at the occupation and/or the CBSA levels.

[23]Burning Glass's 2016 summary report: https://www.burning-glass.com/wp-content/uploads/State_American_Internships_2016.pdf (last seen 25 January 2020).

D. Regression Analysis

The baseline model we employ to analyze the determinants of firm responses is

$$positive_{i,j,l} = \gamma_0 + \gamma_1 c_i + \gamma_2 x_j + \gamma_3 z_l + \varphi_l + \eta_{i,j,l} \quad (2)$$

The subscripts i, j, and l index applicants, ads, and the labor market (CBSA) in which the firm is located, respectively. The variable $positive_{i,j,l}$ equals one when applicant receives a positive response from an employer and zero otherwise. Applicant characteristics, c_i, include dummy variables for major fields of study, grade point average category, types of work experience accumulated while the applicant is completing their degree, the distance from the internship from their university (in miles), and a dummy variable for having a distinctly black-sounding name. The vector of characteristics of the internship, x_j, includes dummy variables for paid and part-time status, the kinds of skills required (based on its predicted detailed occupation), as well as the log of the occupational match score, and an indicator if the ad appeared in both the fall 2015 and spring 2016 waves of the audit.[24] We include a vector of labor market characteristics, z_l, which includes the unemployment rate at the time of our application, and the log of the total college enrollment within 100 miles. We also include a labor market fixed effect, φ_l.[25] The baseline disturbance term

[24] Our experimental design does not guard against submitting more than one resume to the same opening, as random selection of the internship occurs at the applicant-major-university-semester level, and in some cases the target cities are the same across the applicant-major-university clusters. As a consequence, it is likely that some overlap in submissions would occur randomly. In fact, only 34 percent of the randomly selected postings receive one resume; 22 percent received two; around 14 percent received three; another 20 percent received either four, five or six; and the remaining 10 percent received seven or more. Including ad fixed effects eliminates the prospect of studying the effects of ad characteristics on callback rates, but adding these controls provides a useful sensitivity check for the estimated effects of the applicant characteristics. Overall, our findings are robust to the inclusion of ad fixed effects.

[25] We do not include the minimum wage variable from the paid incidence analysis because there is too little variation to be included along with labor market fixed effects. The additional variation in the paid incidence analysis comes from the assignment of the prevailing minimum wage at the posting date.

$\eta_{i,j,l}$ represents variables not accounted for in equation (2), but variations with different fixed effects are presented. The γ_k are the parameters of interest. We present estimates using ordinary least squares with cluster-robust standard errors using two-way clustering on the University × Semester and CBSA.

In Table 6, we present the estimates based on variations of equation (2). Column (1) presents estimates from an augmented version of equation (2) that includes university fixed effects (not shown, per our IRB agreement) in addition to labor market fixed effects. Consistent with the unconditional results in Table 5, applicants to paid internships receive about four percentage points fewer callbacks (recall that the unconditional callback rate for unpaid internships is about 7 percent). Paid internships likely receive more applicants than unpaid internships and need to search less for a suitable applicant who will accept the internship. The required skills for the internship seem to make little difference to the firms' response rate, but we find that as the ad is more specifically related to an occupation the response rate decreases. If the ad was applied to in both the fall and spring semester the response rate was also lower, by about 2.7 percentage points.

As with our analysis of paid status above, we find a distinct link between the regular labor market and the market for interns. Even conditional on labor market fixed effects, firms in labor markets with higher unemployment rates are less likely to contact candidates, with each percentage point increase in the unemployment rate lowering the probability of positive firm response by about 5 percentage points. Not surprisingly, we find that firms are less likely to respond to applicants who are farther away, with a 30 percent increase in distance leading to approximately a 0.4 percentage point decrease in the probability of a positive response from the firm.

In our experimental design, we randomly assigned a variety of types of college work experience to the applicants' profiles, including working in a restaurant, working in retail, and working for a volunteer organization. The restaurant jobs include working as a server at a U.S.-wide chain as well as working in a sandwich shop. The retail jobs include working as a sales representative and working in a clothing store. Lastly, students assigned university-based jobs either work for dining services or at the campus recreation center.[26] Most importantly, we also randomized whether the applicant had any previous internship experience, clearly denoted with the words "Intern" or "Internship". Applicants were assigned zero or one of the types of college work experience, which was not mutually exclusive with whether they were assigned as having an internship, i.e. an applicant could potentially have both work experience and an internship on their résumé. None of the conventional kinds of student employment has an effect on receiving a positive firm response.[27] We find, however, that previous internship experience has a statistically significant effect on the chances of receiving a positive employer response, increasing the probability of a response by 1.1 percentage points.

We find that student performance monotonically affects firm responses (better GPAs lead to higher response rates) and that choice of major affects call back rates. The reference major in the regression is Economics. All other majors are more likely to receive positive responses, with Business Administration and English (both around 1.8 percentage points) being statistically significantly different from zero. Somewhat surprisingly, data analysis skills do not seem to affect the probability of a positive response.

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[26] In our econometric models, we collapse the six types of college work experience into three bins. When we examine the effects of each type of work experience separately, we find the type of work experience completed while in college does not affect callback rates.

[27] In the Data Appendix, we show two resumes, one with internship experience and the other without internship experience (Figure A1).

Like most audit studies, we also find that the black-sounding names on our profiles receive substantially fewer positive responses from firms. The profiles with distinctively black-sounding names receive 1.7 percentage points fewer positive responses relative to an unconditional positive response rate of 6.7 percent for observationally equivalent profiles with white-sounding names.[28]

In the design of our study, we chose which internships to apply for by first looking within a set of 3 target cities for each of the 24 universities that were assigned our résumés. In column 2 of Table 6, we include University × Target City fixed effects rather than just university fixed effects and perform the same regression as in column 1. The results are essentially unchanged. In column 3, we further interact the four names with the University × Target City fixed effects, in which the dummy variable for having a distinctively black name is not identified. The point estimates in column 3 are extremely similar to those in the other two columns. The large number of additional fixed effects add little to the explanatory power of model 1, with partial R^2's of 0.005 and 0.028 for columns 2 and 3, respectively.

We find important differences across types of internships -- part time and unpaid, part time and paid, fulltime and unpaid, and fulltime and paid. In Table 7, we estimate the same model as in column 2 of Table 1 (i.e. with University × Target City fixed effects) separately for the four types of internships in columns 1 through 4, respectively. By design, the number of observations is spread (roughly) equally across all four groups, and they are approximately equally powered. We find that the log of the match score, which we interpret as the specificity of the internship with

[28] The callback rates for the individual white-sounding names, Wyatt and Colin, are statistically indistinguishable from each other. There is, however, a statistical difference in callback rates between the two black-sounding names, Xavier and Darius. Relative to that for Darius, the callback rate for Xavier is about 1.3 percentage points lower. Even though Xavier has a lower callback rate than Darius, both face lower callback rates relative to the white-sounding names, as Darius's callback rate is about 1 percentage point lower and Xavier's is about 2.3 percentage points lower than that for the two white-sounding names.

respect to a particular occupation, is negatively related to a positive response from firms only for unpaid internships, i.e. the more closely the internship matches a specific occupation, the less likely the firm is to respond positively. This may be because firms look for specific qualifications in candidates for such positions. We also find that the unemployment rate is statistically significantly related to firm responses for unpaid internships only. To the extent that full time paid internships are similar to regular jobs, the lack of relationship between the local unemployment rate and callbacks is similar to the results of Farber, Silverman, and von Wachter (2017).

The result that previous internships are important for getting a second internship seems to be driven primarily by unpaid internships in columns 1 and 2, where having had a previous internship raises the probability of a positive firm response by about 2.5 percentage points, double the size of the result for all internships. We can only speculate on the reason for the difference with paid internships, but having a previous internship may signal that a student has the financial resources to be able, or is at least willing, to accept an unpaid internship. As shown in Table 5, location inquires to the applicant are much more likely for unpaid internships, which may also indicate that firms are concerned about students' abilities or willingness to accept an unpaid internship.[29]

In contrast to the results in Table 6, we find that retail jobs and other kinds of employment have a statistically significant and *negative* effect on firm responses for unpaid, part-time internships, which they have a negligible effect on the callback probability for the three other types

[29] Location inquiries tended to include a brief statement about the applicant's location in relation to the firm's location. Examples of such inquires include the following responses: (1) "Hi Xavier, where will you be living this summer? Our internship requires interns to be in the office twice a week and our office is located in [location]. Thanks." (2) "Darius, Thanks for your response. Are you located in [location]?" (3) "Hi Xavier, Thanks for your interest in the Marketing and Sales internships at [firm name]. Is there any chance that you'll be in [location] over the summer?"

of internships. Perhaps because of lack of statistical power, we find that majors have few statistically significant effects on callbacks, except for business administration, which positively affects the chances of a positive response for paid, full-time internships.

Black sounding names negatively affect positive firm responses for all four types of internships, with paid/full-time the only category not statistically significant. The point estimates are larger for unpaid internships, however. As with having had a previous internship, this may reflect firms' expectations about students' financial ability to accept an unpaid internship to the extent that they expect that blacks may come from less-privileged households. The résumés with black sounding names were also more likely to receive location inquiries from firms.[30]

VI. Conclusion

To our knowledge, this is the first study of the market for internships. By examining the content of over 30,000 internship ads, we document key characteristics of internships in the United States, finding that the majority of internships are unpaid and part time. Jobs that are more closely aligned with an occupation, as measured by the machine-learning generated match score are more likely to be paid. We find strong evidence that paid internships are less likely to occur when the regular labor market for young workers has a higher unemployment rate or a minimum wage that

[30] The rate at which firms inquire about an applicant's location is about 0.5 percentage points higher for black-sounding names than for white-sounding names. Applicants with prior internship received location inquiries at a higher rate than those without such experience (about 0.4 percentage points). The overall effect of internship experience on location inquiries appears to be driven by those with a research focus. In addition, location inquiries associated with black-sounding names and past internship experience tend to come from firms seeking unpaid interns. These results are available from the authors by request.

is above the federal level, suggesting a strong link between the market for interns and the labor market more generally.

To understsand how students and internship characteristics affect firms' responses (and, presumably, students' success in acquiring an internship), we conducted an audit study with around 11,000 résumés submitted. As with our descriptive analysis of the demand for interns, we found a strong link with the regular labor market, which appears to be driven by unpaid internships. Previous internship experience is one of the key determinants of success in the internship market, which raises the question of how students should get their first internship experience. As with the link with the regular labor market, this appears to be primarily driven by unpaid internships. The negative impact that having a black-sounding name has on call back rates is greatest for unpaid internships. All three of these results suggest that firms offering unpaid internships may be sensitive to indications that students can financially affford to accept an such an internship. Emerging research (Jaeger, Nunley, and Seals 2020) suggests that internships may be an important determinant of post-college labor market success. To the extent that firms are less likely to respond to students who appear less likely to afford an unpaid internship, differences in labor market success after college could partially be driven by lack of internship opportunities during college.

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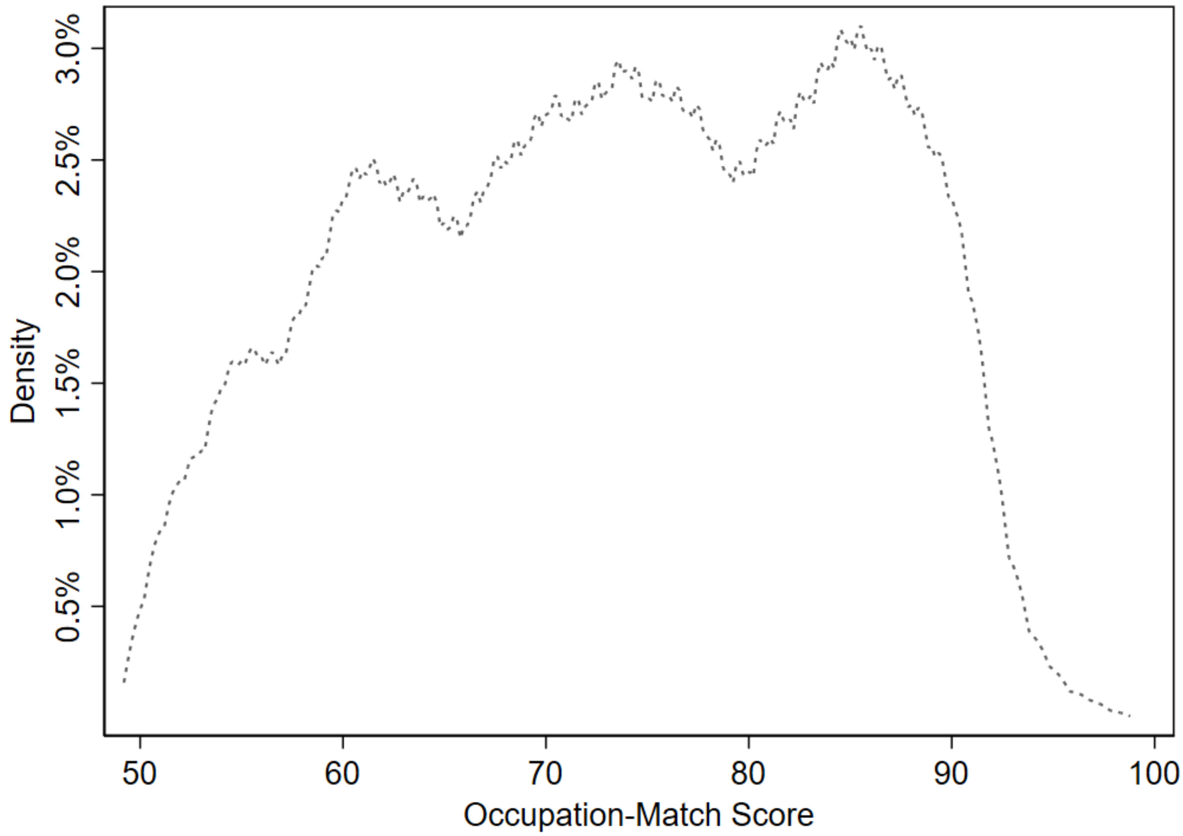
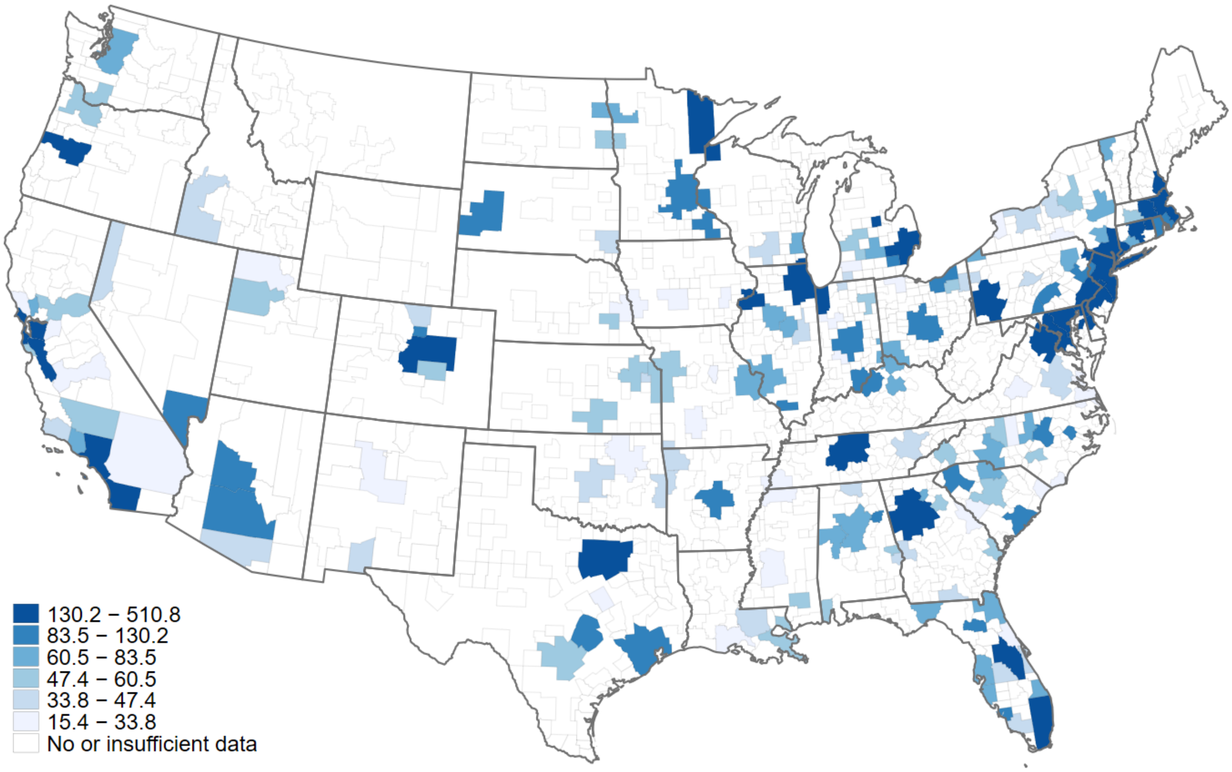
Figure 1
Kernel Density Estimate for the Occupation-Match Score



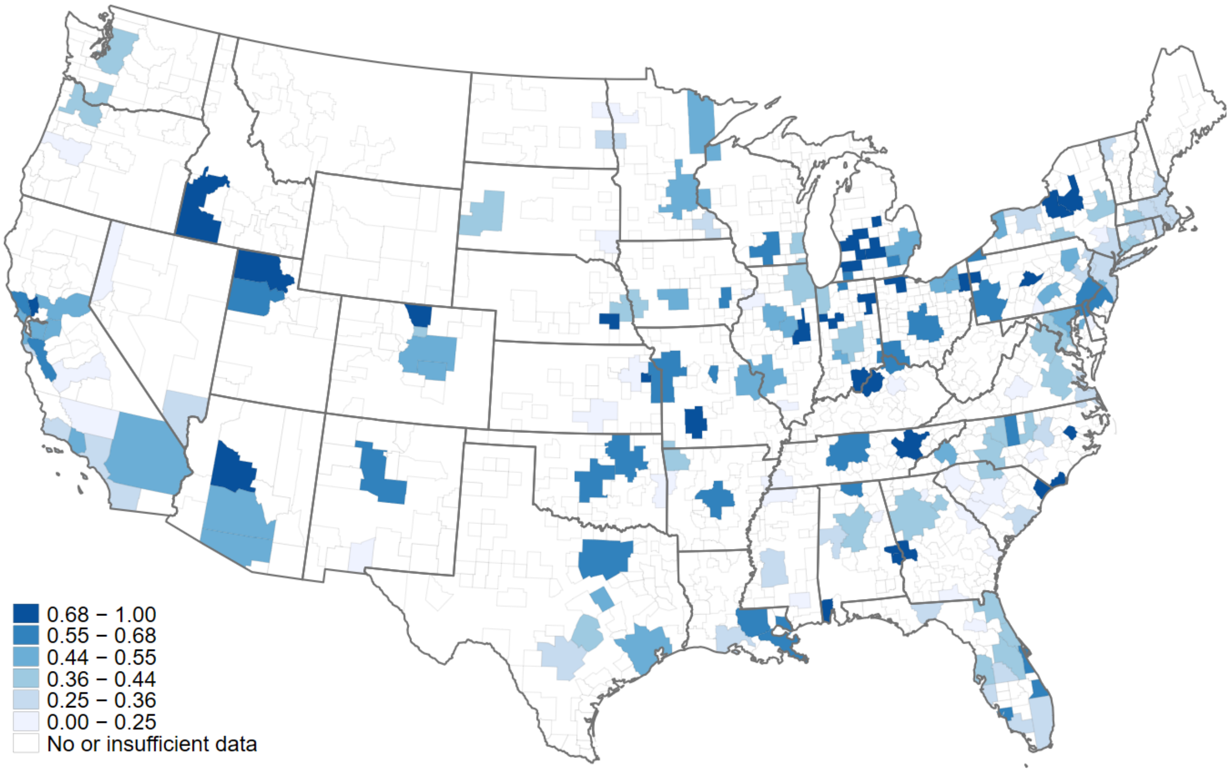
Note: Using the full sample of ads (*N* = 28,551), the figure plots the kernel density estimate for the occupation-match, which ranges in value from 50 to 99.

Figure 2
Internships per 100,000 18-25 Year-Olds by CBSA



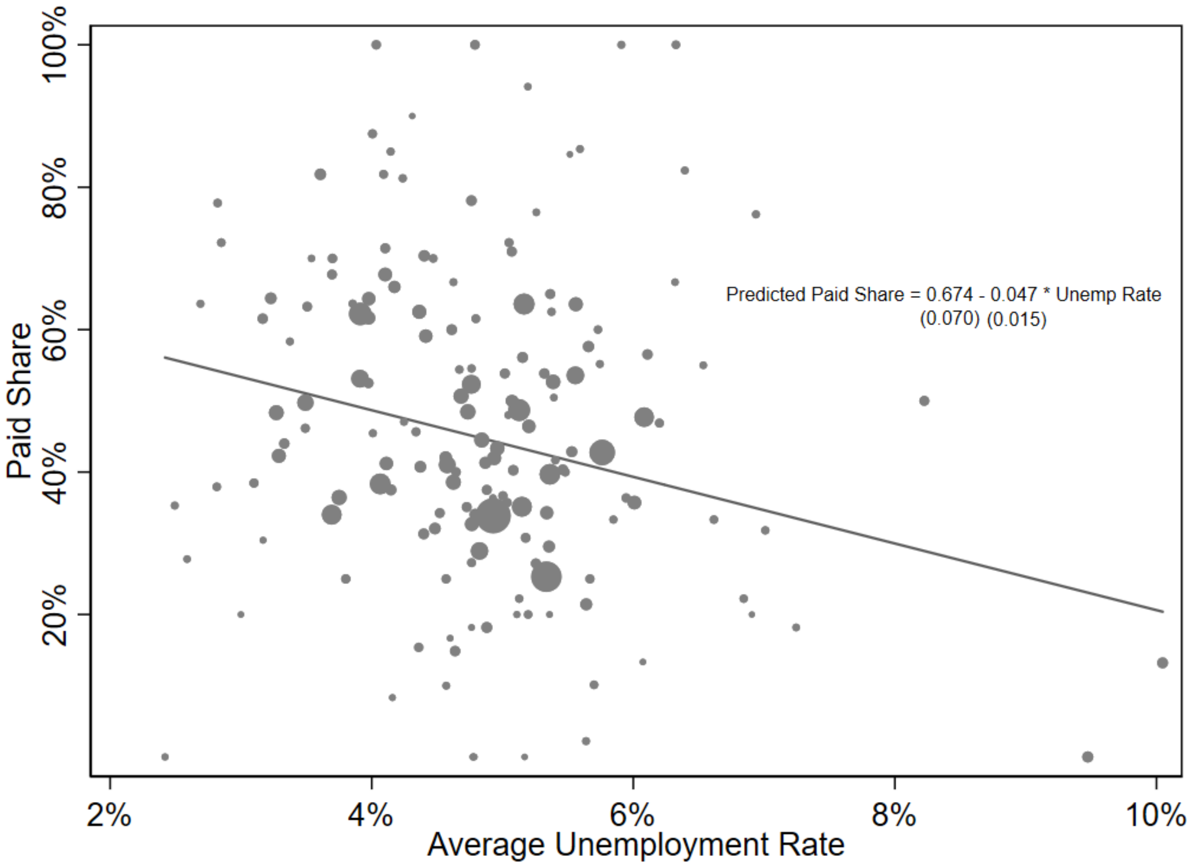
Notes: The figure presents a heat map of internships per 100,000 18-25 year-olds by CBSA. Lighter colors indicate fewer internship ads per capita, and darker colors indicate a denser concentration of internship advertisements in the CBSA. CBSAs shaded white represent areas with zero or less than 10 internships ads posted overall. The heat map is based on the full sample of internship advertisements (N = 28,551) aggregated to the CBSA level (N = 161). In our sample, around 75% of CBSAs had at least one internship advertised on the website during our two webscrapings. The sample is, however, limited to CBSAs with at least 10 unique internships posted on the website at the two webscraping dates (November 2016, March 2017).

Figure 3
Paid Share by CBSA



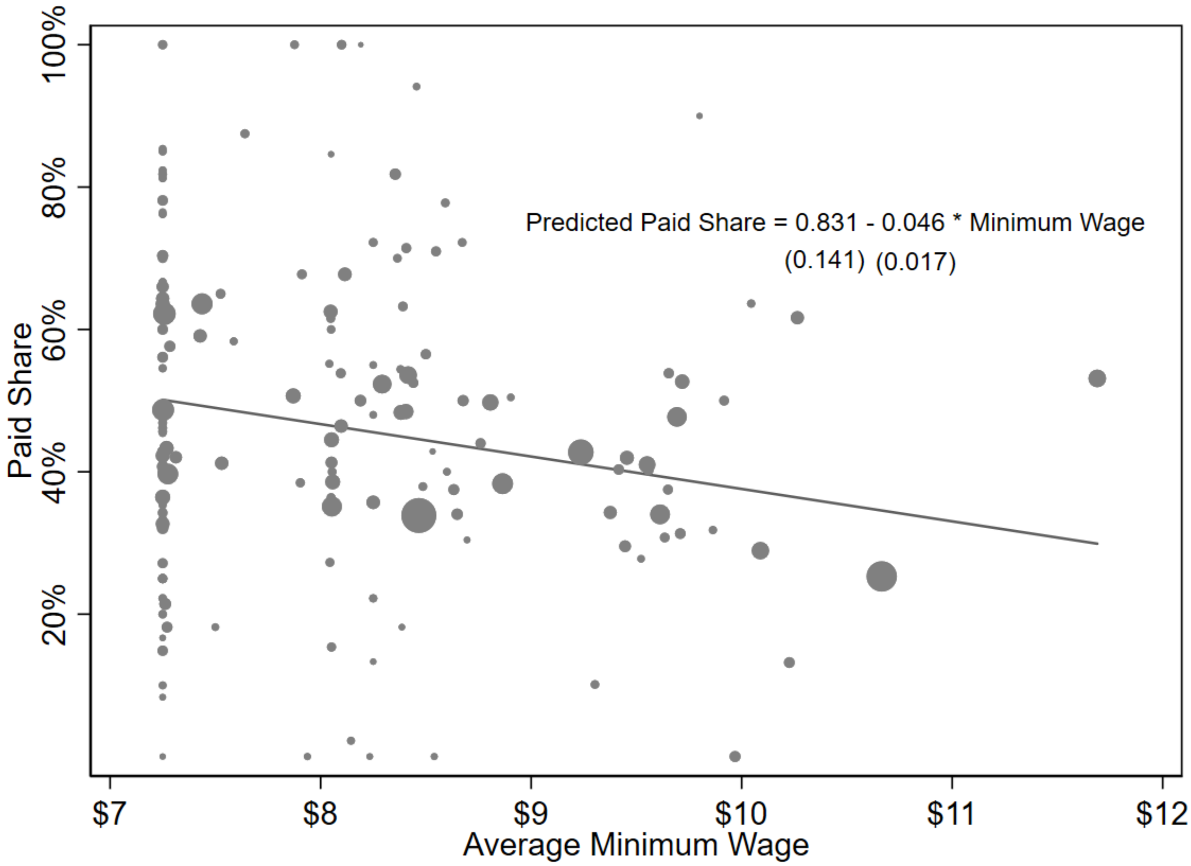
Notes: The figure presents a heat map of the paid share of internships by CBSA. Lighter colors indicate a lower paid share, and darker colors indicate a higher share of internships that are paid. CBSAs shaded white represent areas with either no paid internships or there are fewer than 10 internships advertisements overall. The heat map is based on the full sample of internship advertisements (*N* = 28,551) aggregated to the CBSA level (*N* = 161). We limit the sample to CBSAs with at least 10 unique internships posted on the website at the two webscraping dates (November 2016, March 2017).

Figure 4
Paid Share and Unemployment



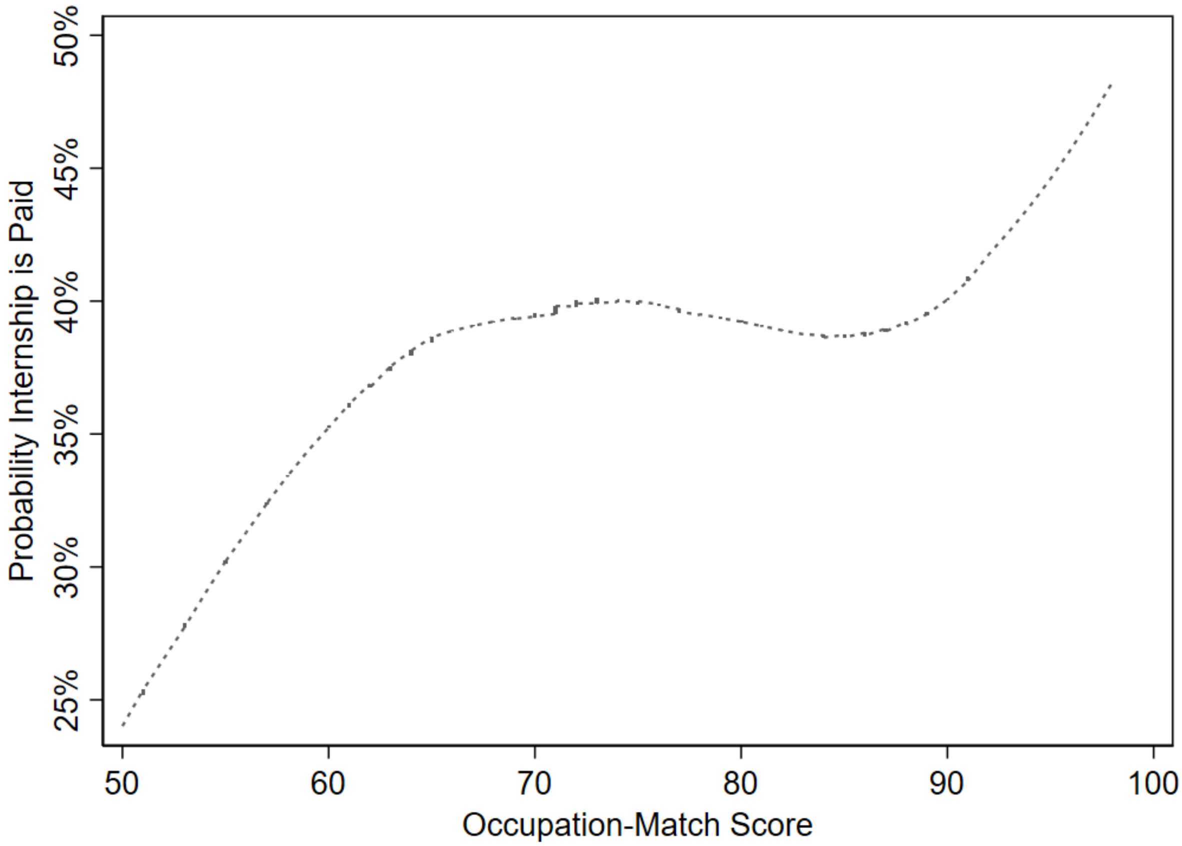
Notes: The figure shows the paid share if internships posted in 2015 and 2016 plotted against the average unemployment rate over the 2015-2016 period. Using the full sample of ads (N = 28,551) aggregated to the CBSA level (N = 161), we present a scatterplot with a linear fit through the data points. The average sizes of the 18-25 year-old population over 2015 and 2016 by CBSA are used as sampling weights. The sample includes CBSAs with at least 10 internship ad postings observed in either the fall or spring web-scrapings, but is limited to ads posted in 2015 and 2016.

Figure 5
Paid Share and Minimum Wages



Notes: Aggregating to the CBSA level (N = 161), the figure shows the paid share of internships plotted against the average minimum wage. The sample includes CBSAs with at least 10 internship ad postings observed in either the fall or spring web-scrapings. The average sizes of the 18-25 year-old population over 2015 and 2016 by CBSA are used as sampling weights.

Figure 6
Occupation-Match Score and Paid Status



Notes: The figure plots the relationship between the occupation-match score and the probability an internship is paid using locally weighted regression. The full sample of ads is used (*N* = 28,551).

Table 1
Cross Tabulation Between Paid/Unpaid and Part-Time/Full-Time Statuses

	Part-Time Internships	Full-Time Internships	All Internships
	(1)	(2)	(3)
Unpaid Internships	53.71% [15,334]	8.00% [2,283]	61.70% [17,617]
Paid Internships	18.60% [5,311]	19.69% [5,623]	38.30% [10,934]
All Internships	72.31% [20,645]	27.69% [7,906]	100.00% [28,551]

Notes: The numbers of observations in each cell are provided in brackets below the percentages. The null hypothesis of independence between unpaid/paid and part-/full-time internships is rejected (Pearson χ^2 statistic $= 5{,}000$).

Table 2
Classification of Ads to Major Occupation Categories

Major Occupation Group	Percentage of Ads Assigned (1)	Percentage Paid (2)	Percentage Part Time (3)
Management	6.0%	49.3%	59.6%
Business and Financial Operations	21.7%	36.7%	74.6%
Computer and Mathematical	6.0%	43.7%	65.5%
Architecture and Engineering	0.8%	57.7%	57.7%
Life, Physical, and Social Science	0.7%	23.0%	70.6%
Community and Social Services	4.0%	19.2%	81.3%
Legal	0.6%	19.0%	77.7%
Education, Training, and Library	2.4%	26.9%	86.1%
Arts, Design, Entertainment, Sports, and Media	31.4%	23.3%	84.3%
Healthcare Practitioners and Technical	0.4%	39.4%	71.2%
Healthcare Support	0.3%	20.7%	80.4%
Protective Service	0.1%	31.6%	79.0%
Food Preparation and Serving Related	0.5%	38.6%	68.2%
Building and Grounds Cleaning and Maintenance	0.1%	30.0%	70.0%
Personal Care and Service	0.8%	27.1%	72.9%
Sales and Related	14.2%	72.4%	46.0%
Office and Administrative Support	9.2%	44.1%	72.5%
Farming, Fishing, and Forestry	0.1%	33.3%	56.7%
Construction and Extraction	0.1%	55.9%	67.7%
Installation, Maintenance, and Repair	0.1%	46.7%	66.7%
Production	0.7%	24.9%	79.9%
Transportation and Material Moving	0.1%	40.0%	72.0%

Notes: The full sample of 28,551 internship advertisements is used. The major occupation groups listed are based on the 2010 major (2 digit) standard occupation classification (SOC) system.

Table 3
Determinants of Paid Status

Explanatory Variable	Part- and Full-Time Internships (1)	(2)	(3)	(4)	Part-Time Internships (5)	Full-Time Internships (6)
Part Time	-0.3915***	-0.3518***	-0.3366***	-0.3211***	--	--
	(0.0324)	(0.0295)	(0.0243)	(0.0258)	--	--
Social Skill Tasks	0.0040	-0.0107	-0.0109	--	-0.0231**	0.0286**
	(0.0165)	(0.0110)	(0.0095)	--	(0.0099)	(0.0120)
Routine Tasks	0.0067	-0.0160	-0.0127	--	-0.0209*	0.0172
	(0.0165)	(0.0146)	(0.0131)	--	(0.0125)	(0.0179)
Nonroutine Cognitive Tasks	0.0449***	0.0230**	0.0210**	--	0.0199	0.0139
	(0.0126)	(0.0100)	(0.0092)	--	(0.0130)	(0.0090)
Occupation Match Score ≥ 90	0.0519**	0.0759***	0.0628***	0.0435**	0.0564**	0.0791***
	(0.0250)	(0.0215)	(0.0209)	(0.0188)	(0.0262)	(0.0191)
Occupation Match Score between 60 and 90	0.0525***	0.0564***	0.0478***	0.0366**	0.0531***	0.0387*
	(0.0158)	(0.0153)	(0.0162)	(0.0146)	(0.0170)	(0.0231)
Unemployment Rate	-0.0391***	-0.0371***	-0.0351**	-0.0297**	-0.0281*	-0.0632**
	(0.0095)	(0.0089)	(0.0145)	(0.0116)	(0.0168)	(0.0265)
Minimum Wage	-0.0225***	-0.0207***	-0.0175***	-0.0140***	-0.0157***	-0.0265***
	(0.0053)	(0.0056)	(0.0052)	(0.0038)	(0.0043)	(0.0086)
Log of 4-Year Enrollment within 100 Miles of Firm	-0.0212***	-0.0209***	-0.0038	-0.0024	-0.0067	0.0003
	(0.0078)	(0.0076)	(0.0058)	(0.0054)	(0.0055)	(0.0094)
Ad Posted in Fall	-0.0319*	-0.0341**	-0.0452**	-0.0595***	-0.0371*	-0.0504
	(0.0180)	(0.0156)	(0.0174)	(0.0151)	(0.0221)	(0.0378)
Ad Posted in Fall and Spring	0.0779***	0.0712***	0.0804***	0.0863***	0.0948***	0.0389**
	(0.0244)	(0.0238)	(0.0231)	(0.0213)	(0.0351)	(0.0189)
Fixed Effects Included:						
2-Digit SOC	No	Yes	Yes	No	Yes	Yes
6-Digit SOC	No	No	No	Yes	No	No
CBSA	No	No	Yes	Yes	Yes	Yes
R^2	0.2143	0.2501	0.2858	0.3391	0.1260	0.2339
N	28,424	28,424	28,424	28,424	20,554	7,805

Notes: Point estimates are marginal effects. Standard errors with two-way clustering on occupations and CBSAs are provided in parentheses. *, **, and *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively. The numbers of observations differ from that of the full sample shown in Tables 1 and 2. The inclusion of CBSA fixed effects in columns 3-6 results in the elimination of 127 observations due to perfect collinearity. To facilitate comparisons across specifications, we use the same sample for the estimates in columns 1 and 2 as is used to compute those in columns 3-6.

Table 4
Summary Statistics for Résumé Credentials

		Part-Time Internships		Full-Time Internships	
	All Internships	Unpaid Internships	Paid Internships	Unpaid Internships	Paid Internships
Resume Credential	(1)	(2)	(3)	(4)	(5)
Internship Experience	0.502	0.505	0.499	0.515	0.488
	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)
Volunteer Experience	0.501	0.500	0.509	0.505	0.490
	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)
Employed in Retail	0.332	0.329	0.335	0.335	0.330
	(0.471)	(0.470)	(0.472)	(0.472)	(0.470)
Employed in Restaurant	0.334	0.340	0.324	0.340	0.334
	(0.472)	(0.474)	(0.468)	(0.474)	(0.472)
Business Admin. Major	0.167	0.170	0.170	0.166	0.163
	(0.373)	(0.376)	(0.376)	(0.372)	(0.369)
Psychology Major	0.166	0.171	0.164	0.171	0.159
	(0.372)	(0.376)	(0.370)	(0.377)	(0.366)
Biology Major	0.166	0.167	0.175	0.162	0.160
	(0.372)	(0.373)	(0.380)	(0.369)	(0.367)
Marketing Major	0.166	0.165	0.165	0.165	0.171
	(0.373)	(0.371)	(0.371)	(0.371)	(0.377)
English Major	0.167	0.167	0.166	0.159	0.177
	(0.373)	(0.373)	(0.372)	(0.365)	(0.382)
GPA (3.4 or 3.6)	0.334	0.335	0.330	0.341	0.329
	(0.472)	(0.472)	(0.470)	(0.474)	(0.470)
GPA (3.8 or 4.0)	0.334	0.328	0.332	0.333	0.345
	(0.472)	(0.470)	(0.471)	(0.472)	(0.475)
Data Analysis	0.667	0.657	0.679	0.663	0.663
	(0.472)	(0.475)	(0.467)	(0.473)	(0.473)
Black	0.499	0.497	0.508	0.497	0.492
	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)
Observations	11,035	2,720	2,811	2,735	2,769

Notes: The sample means for each resume characteristic are provided along with the standard deviation (in parentheses). We collapse some of the resume credentials into categories in an effort to streamline the presentation of the findings. We reduce three different types of internship experience down to one variable; four types of volunteer experience into a single variable; and six different types of college work experience into three separate categories. The omitted category for the college work experiences is employment on campus; the omitted category for the majors is economics; and the omitted category for the GPAs is being assigned a 3.0 or 3.2.

Table 5
Employer Response Rates

		Part-Time Internships		Full-Time Internships	
	All Internships	Unpaid Internships	Paid Internships	Unpaid Internships	Paid Internships
Employer Response	(1)	(2)	(3)	(4)	(5)
Positive Response	0.059	0.083	0.030	0.073	0.050
	(0.235)	(0.276)	(0.170)	(0.260)	(0.218)
Expression of Interest	0.028	0.030	0.015	0.039	0.029
	(0.166)	(0.171)	(0.121)	(0.194)	(0.168)
Interview Request	0.030	0.053	0.015	0.034	0.021
	(0.172)	(0.223)	(0.121)	(0.181)	(0.143)
Location Inquiry	0.014	0.024	0.006	0.020	0.005
	(0.116)	(0.153)	(0.078)	(0.139)	(0.073)
Observations	11,035	2,720	2,811	2,735	2,769

Notes: The "Positive Response" rate includes both expressions of interest and interview requests. Location inquiries are those in which the advertising establishment/firm asked about the applicant's location in relation to the internship opening.

Table 6
Determinants of Callback Rates

	(1)	(2)	(3)
Paid	-0.0378***	-0.0378***	-0.0369***
	(0.0071)	(0.0069)	(0.0067)
Part Time	-0.0068	-0.0072	-0.0064
	(0.0049)	(0.0050)	(0.0057)
Social Skill Tasks	0.0016	0.0014	0.0012
	(0.0022)	(0.0023)	(0.0023)
Nonroutine Cognitive Tasks	-0.0026	-0.0026	-0.0029
	(0.0021)	(0.0021)	(0.0022)
Routine Tasks	0.0004	0.0000	-0.0003
	(0.0029)	(0.0030)	(0.0029)
Log of Occupation Match Score	-0.0859***	-0.0872***	-0.0836***
	(0.0133)	(0.0141)	(0.0126)
Unemployment Rate	-0.0481***	-0.0492***	-0.0492***
	(0.0148)	(0.0145)	(0.0139)
Log College Enrollment	-0.0004	-0.0003	-0.0003
within 100 Miles of Firm	(0.0026)	(0.0032)	(0.0031)
Log of Distance of Applicant	-0.0122***	-0.0081	-0.0081
from Firm (in miles)	(0.0028)	(0.0169)	(0.0167)
Internship Experience	0.0115***	0.0110***	0.0117***
	(0.0037)	(0.0037)	(0.0038)
Volunteer Experience	0.0004	0.0002	0.0000
	(0.0040)	(0.0041)	(0.0047)
Worked in Retail	-0.0076	-0.0074	-0.0062
	(0.0081)	(0.0078)	(0.0083)
Worked in Restaurant	-0.0079	-0.0073	-0.0071
	(0.0052)	(0.0053)	(0.0055)
Business Administration Major	0.0183*	0.0169*	0.0154
	(0.0092)	(0.0092)	(0.0099)
Psychology Major	0.0004	-0.0000	-0.0028
	(0.0069)	(0.0067)	(0.0066)
Biology Major	0.0079	0.0073	0.0057
	(0.0116)	(0.0117)	(0.0116)
Marketing Major	0.0081	0.0085	0.0071
	(0.0092)	(0.0091)	(0.0090)
English Major	0.0182*	0.0191*	0.0172
	(0.0108)	(0.0103)	(0.0107)
GPA (3.4 or 3.6)	0.0076	0.0078	0.0051
	(0.0067)	(0.0055)	(0.0050)
GPA (3.8 or 4.0)	0.0105*	0.0100*	0.0073
	(0.0058)	(0.0052)	(0.0048)
Data Analysis	-0.0018	-0.0021	-0.0011
	(0.0043)	(0.0043)	(0.0043)
Black	-0.0170***	-0.0172***	0.0000
	(0.0036)	(0.0036)	(0.0000)
Spring Semester	-0.0051	-0.0040	-0.0037
	(0.0046)	(0.0043)	(0.0042)
Ad Posted in Fall and Spring	-0.0273***	-0.0281***	-0.0274***
	(0.0058)	(0.0061)	(0.0064)
Fixed Effects Included:			
CBSA	Yes	Yes	Yes
University	Yes	No	No
University × Target City	No	Yes	No
Name × University × Target City	No	No	Yes
R^2	0.0354	0.0401	0.0624
N	10,988	10,988	10,988

Notes: Point estimates are marginal effects. Standard errors with two-way clustering on University × Semester and CBSAs are in parentheses. *, **, and *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively. The numbers of observations differ from that shown in Tables 4 and 5. The inclusion of CBSA fixed effects results in the elimination of 47 observations due to perfect collinearity.

Table 7
Determinants of Callback Rates by Paid/Unpaid and Part-Time/Full-Time Statutes

	Part-Time Internships		Full-Time Internships	
	Unpaid Internships	Paid Internships	Unpaid Internships	Paid Internships
	(1)	(2)	(3)	(4)
Social Skill Tasks	0.0009	-0.0053	-0.0013	0.0051
	(0.0051)	(0.0034)	(0.0078)	(0.0067)
Nonroutine Cognitive Tasks	-0.0145***	0.0010	-0.0050	0.0016
	(0.0049)	(0.0019)	(0.0064)	(0.0037)
Routine Tasks	0.0061	-0.0078**	-0.0040	0.0048
	(0.0065)	(0.0030)	(0.0061)	(0.0073)
Log of Occupation Match Score	-0.0687***	-0.0604**	-0.1508***	-0.0365
	(0.0218)	(0.0226)	(0.0397)	(0.0269)
Unemployment Rate	-0.1248***	0.0006	-0.0875***	0.0299
	(0.0322)	(0.0238)	(0.0236)	(0.0271)
Log College Enrollment within 100 Miles of Firm	-0.0008	0.0027***	0.0114***	-0.0096
	(0.0041)	(0.0008)	(0.0033)	(0.0072)
Log of Distance of Applicant from Firm (in miles)	-0.0169***	-0.0072**	-0.0147**	-0.0101*
	(0.0053)	(0.0027)	(0.0058)	(0.0056)
Internship Experience	0.0252	0.0211***	0.0076	-0.0022
	(0.0168)	(0.0066)	(0.0061)	(0.0092)
Volunteer Experience	-0.0061	0.0040	0.0013	-0.0032
	(0.0142)	(0.0092)	(0.0074)	(0.0118)
Worked in Retail	-0.0349*	-0.0032	0.0046	0.0045
	(0.0191)	(0.0080)	(0.0142)	(0.0093)
Worked in Restaurant	-0.0393**	0.0026	0.0148	-0.0075
	(0.0167)	(0.0092)	(0.0126)	(0.0100)
Business Administration Major	-0.0002	0.0134	0.0312	0.0270*
	(0.0189)	(0.0088)	(0.0222)	(0.0148)
Psychology Major	-0.0074	-0.0003	-0.0071	0.0198
	(0.0184)	(0.0097)	(0.0240)	(0.0147)
Biology Major	0.0032	0.0044	0.0017	0.0218
	(0.0215)	(0.0113)	(0.0220)	(0.0184)
Marketing Major	-0.0110	0.0119	0.0086	0.0166
	(0.0164)	(0.0152)	(0.0163)	(0.0139)
English Major	0.0238	0.0092	0.0315	0.0122
	(0.0191)	(0.0126)	(0.0216)	(0.0154)
GPA (3.4 or 3.6)	0.0097	0.0091**	0.0049	0.0069
	(0.0181)	(0.0043)	(0.0131)	(0.0118)
GPA (3.8 or 4.0)	0.0147	0.0044	0.0139	0.0105
	(0.0114)	(0.0077)	(0.0117)	(0.0080)
Data Analysis	-0.0057	0.0009	0.0053	-0.0091
	(0.0107)	(0.0052)	(0.0085)	(0.0065)
Black	-0.0245**	-0.0223***	-0.0154*	-0.0083
	(0.0099)	(0.0056)	(0.0084)	(0.0084)
Spring Semester	-0.0137*	0.0037	-0.0095	0.0019
	(0.0078)	(0.0064)	(0.0072)	(0.0087)
Ad Posted in Fall and Spring	-0.0222	-0.0110	-0.0353***	-0.0178
	(0.0281)	(0.0100)	(0.0112)	(0.0107)
R^2	0.0555	0.0460	0.0627	0.0536
N	2,708	2,798	2,712	2,750

Notes: Point estimates are marginal effects. Standard errors with two-way clustering on University × Semester and CBSAs are in parentheses. *, **, and *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively. Each specification includes CBSA and University fixed effects, although the estimated effects of the explanatory variables are robust to the inclusion of University × Target City or Name × University × Target City fixed effects.

Data Appendix

A1. Advertisement Data

In November 2016 again in March 2017, we pulled all internship ads posted on a prominent internship/jobs online board. Ads posted in November 2016 totaled 28,740, and the analogous figure for March 201 is 14,579 ads. Thus, in total, our raw sample consists of 43,319 ads.

The ads provide the following information about the internship opening: position title, firm name, firm address, posting date of the ad, part-time/full-time status, paid/unpaid status, the description of the internship, the responsibilities of the intern, and the skills required of the intern. We use all of the information in the ads for various purposes, which are described in more detail in subsections that follow.

A1.1. Assigning O*NET-SOC Codes

We use the O*NET-SOC AutoCoder, a proprietary machine learning algorithm (MLA),[1] to assign the internship ads an O*NET-SOC code, which is a based on the Standard Occupational Classification (SOC) system.[2] The MLA, which was funded by the U.S. Department of Labor's Employment and Training Administration, divides the text of the ad into individual analyst-weighted terms,[3] then assigns an O*NET-SOC code based on how well the differentially-weighted words used in the ad correspond to the detailed descriptions of the occupation in the Occupational Information Network (O*NET) database.[4] In our case, the internship title and description are used as inputs in the MLA, which was able to assign an O*NET-SOC code to 88 percent of the ads. In total, 5,474 of the ads were not assigned an O*NET-SOC code. Because our analysis uses the "match score" generated by the MLA as an explanatory variable of paid/unpaid status, we exclude ads that could not be assigned an O*NET-SOC code. Eliminating these observations reduces the sample size to 37,845 ads.

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[1] A free version of the O*NET-SOC AutoCoder can be found at: https://www.O*NETsocautocoder.com/plus/O*NETmatch (last seen November 2018).

[2] For more information on the SOC system see https://www.bls.gov/soc/ (laset seen January 2020).

[3] The frequently-asked questions (FAQs) page available on the O*NET-SOC AutoCoder website provides additional information regarding how the O*NET-SOC AutoCoder works. Given that the algorithm is proprietary, it is not possible to provide extensive detail on algorithm's parameters. The FAQs web address is https://www.O*NETsocautocoder.com/plus/O*NETmatch?action=guide (last seen November 2018).

[4] Career Builder, a large online job board, recently used the same algorithm to label job advertisements to be used in the classification of job titles for the creation of a large training data set (Javed et. al 2015). Career Builder's algorithm, Carotene, marks a slight improvement on the Autocoder application with respect to classifying past work histories of job seekers, but it is inconclusive on whether the algorithm outperforms Autocoder on classifying jobs ads. Also of importance is that the taxonomy used in the Carotene algorithm is of finer granularity, and not consistent with the current O*NET taxonomy. Thus, we concluded that use of the Autocoder algorithm was the most appropriate choice in the classification of the internship jobs ads from the experiment.

A1.2. Geographic Location of Advertising Firms and Labor Market Conditions

After limiting the sample to ads assigned O*NET-SOC codes, we use the Open Cage geocoder (http://geocoder.opencage.com, last seen 19 March 2017) through the `opencagegeo` STATA module to geocode the addresses of the advertising firms. In the end, we incorporate variables measured at the city, core-based-statistical areas (CBSAs) or New England City and Town Areas (NECTAs),[5] and state levels.

The city is typically provided in the ad posting, but CBSAs/NECTAs are assigned to the the ads using a crosswalk.[6] Using the crosswalk, we assign CBSAs/NECTAs to the ads based on the county in which the firm is located. We match 99 percent of county level FIPS codes to the corresponding CBSA/NECTA codes, lowering the number of ads in the data set from 37,845 to 37,500.

The combination of the area FIPS codes and the posting date allows us to link the ads to the unemployment rates in the CBSAs/NECTAs by the month and year in which the ad was posted online. Most of the ads were posted in 2015 and 2016 (about 91 percent), but some were posted in 2014 (slightly less than 2 percent) and 2017 (slightly more than 7 percent). In practice, we match the area FIPS code for each ad to the database of seasonally adjusted civilian labor force and (un)employment variables from the Bureau of Labor Statistics (BLS).[7]

We eliminate observations for which the unemployment rate is not available, bringing the sample to 36,881 ads. In additional, we also eliminate observations posted prior to 2014 (4 observations) and those posted by firms located in Alaska or Hawaii (79 observations). Thus, the sample is composed of 36,798 ads.

A1.4. Linking Ads to Minimum Wage Data and College Enrollments

We assign the prevailing minimum wage, which vary at the city, county, or state level, to the advertising firm's location. We use two different data sets and a compilation of minimum wage ordinances for cities and counties provided by the University of California at Berkeley Labor Center. The first of the two data sources come from Vaghul and Zipperer (2016), and the final data source is from the Inventory of US City and County Minimum Wage Ordinances from UC Berkeley's Labor Center.[8] Using these sources, we assign the prevailing minimum wage given the firm's location at the ad's posting date. We were able to assign all ads a minimum wage.

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[5] In the paper, we use the CBSA acronym to refer to both CBSAs and NECTAs.

[6] The crosswalk is available at the following website: http://www.nber.org/data/cbsa-msa-fips-ssa-county-crosswalk.html.

[7] The civilian labor force and employment statistics for the metro- and micro-statistical areas come from https://www.bls.gov/lau/metrossa.htm and https://download.bls.gov/pub/time.series/la/la.data.62.Micro, respectively. Some areas in the northeastern U.S. do not provide metro- or micro-statistical area unemployment rates. To remedy this issue, we replace the area FIPS code with the New England City and Town Area (NECTA) codes, which come from the U.S. Census Bureau, and merge the unemployment rates for those areas by NECTA in lieu of the area FIPS code.

[8] The data from Vaghul and Zipperer (2016) can be found at https://equitablegrowth.org/working-papers/historical-state-and-sub-state-minimum-wage-data/, (last seen 1 January 2020), while the data from UC Berekeley's Labor Center can be found at http://laborcenter.berkeley.edu/minimum-wage-living-wage-resources/inventory-of-us-city-and-county-minimum-wage-ordinances/ (last seen 1 January 2020).

College enrollments are assigned to each ad using data from the College Scorecard in 2016-2017.[9] The College Scorecard provides the latitude and longitude of each institution in the database plus the enrollment in 2016-17. For each internship ad in the webscraped and audit data, we calculated the distance to each institution in the College Scorecard data. We then totaled enrollments of those institutions that were within 100 miles of the firm.

A1.4. Linking Ads to O*NET Data

Using data from O*NET 21.1 (released in November 2016), we create variables proxy for the task content of the detailed occupations. We follow Deming (2017) and create three measures of task intensity: social skills task intensity, nonroutine analytical task intensity, and routine task intensity.

To create the measures of routine task intensity, nonroutine analytical task intensity, and social skill task intensity, we follow Deming's (2017) and Autor et al.'s (2003) approach by averaging the values (on a 1-5 scale) for a set of particular survey questions, creating composite variables, and converting those composite variables to a 0-10 scale. The variables are in effect weighted percentile ranks, which range in value from 0-10.

The measure of routine task intensity is based on the average of the following questions: (i) how automated is the job, and (ii) how important is repeating the same physical or mental activities. The measure of nonroutine analytical task intensity is based on the average of the survey questions that gauge the extent to which mathematics and analytical reasoning is used: (i) the extent to which mathematical reasoning is required, (ii) whether mathematical reasoning is required to solve problems, and (iii) whether knowledge of mathematics is required. The social skill intensity measure is based on the average of four skill requirements: (i) coordination, (ii) negotiation, (iii) persuasion, and (iv) social perceptiveness.

The routine task intensity, nonroutine analytical task intensity, and social skill intensity variables are computed at varying SOC levels. That is, we compute these measures by collapsing the O*NET-SOC code to the 3-, 5-, and 6-digit levels. Ideally, we would prefer to merge the O*NET variables and the ad data at the most detailed level (i.e. 6-digit SOC), but that is not possible for all cases. However, the vast majority of ads are matched to the O*NET data set at the 6-digit SOC level (around 97 percent). The imperfect merge results in 858 ads not being assigned the O*NET variables. In lieu of dropping these observations, we simply merge the O*NET variables at a less detailed SOC level. For example, of the 858 ads that could not be merged at the 6-digit level, we merge 776 of these successfully at the 5-digit level, and we merge the remaining 82 ads at the 3-digit SOC level.

A1.6. Computing Number of Words in the Ads

We compute the number of words in the ads as a guard against more detailed ads receiving higher occupation-match scores. If that is the case, the estimated effect of the occupation-match score on paid status could be biased.

Before counting the number of words in the ads, we remove all stop words. To count the words in the ads, we use the `txttools` package available from STATA. In terms of summary

[9] See https://collegescorecard.ed.gov/data/ (last seen 20 January 2020).

statistics, the average number of words in the position description is 84, and the 10^{th}, 25^{th}, 50^{th}, 75^{th}, and 90^{th} percentiles are 25, 42, 68, 109, and 165, respectively. Our findings are robust to the inclusion of controls for the number of words in an ad.

A1.7. Duplicate Ads

Over 40 percent of the ads are duplicates (observed in November 2016 and March 2017). We exclude duplicate ads from our analysis. As such, we eliminate 8,247 ads, bringing the size of the final sample to 28,551 ads. We include a control variable in our regression models that indicates whether the ad had a duplicate at the time of the second webscrape. We have, alternatively, included duplicate ads in the analysis, and our findings are unaffected by the inclusion or exclusion of these observations.

A1.8. Final Sample

The final sample consists of 28,551 internship ads. In Tables 1 and 2, we rely on the entire sample to present summary statistics on unpaid/paid and part-time/full-time status overall (Table 1) and by major occupation category (Table 2). However, in the regression analysis (Table 3), 127 ads are dropped when CBSA fixed are included. The inclusion of CBSA fixed effects introduces a perfectly collinearity problem when the CBSA has two few ads (4 or less). As such, we restrict all specifications presented in Table 3 to ads posted in CBSAs with sufficient identifying variation, which results in the inclusion of 28,424 ads.

A2. Audit Experiment – Incorporating External Data Sources

Using the O*NET-SOC AutoCoder (See Section A1.1), we use the internship title and the internship description as inputs in the machine-learning algorithm to classify the internship ads into detailed occupation categories. We obtain an 8-digit O*NET-SOC code for each ad along with a score that measures how well the ad text matches the characteristics of the detailed occupation (based on characteristics provided by O*NET). Out of the 11,520 applications submitted, we assign all but 466 of the ads a detailed 8-digit O*NET-SOC code. Due to our interest in measuring the task intensity variables (routine task intensity, social skill task intensity, and nonroutine cognitive task intensity), we eliminate applications to ads that could not be assigned an 8-digti O*NET-SOC code. This brings the number of observations in the sample to 11,054.

In terms of matching the ads to the data provided by O*NET, we follow the same process as described above (Section A1.4). That is, we match the ad at the most detailed level possible (preferably 6-digit SOC). We match 10,909 ads at the 6-digit SOC level. Of the 133 ads that did not match the 6-digit level, we match 106 of those at the 5-digit level. The remaining 27 ads are then matched at the 3-digit level.

Like the analysis of the webscraped ads, we incorporate information from other sources, such as CBSA unemployment rates, the distance (in miles) between the university the applicant attends and the location of the firm, and four-year college enrollment within 100 miles of the firm.

We use the university for the applicant's address because all fictive applicants are assigned addresses near campus. For 12 of the ads, we are either unable to determine the CBSA in which the firm is located, and the distance between the applicant and advertising firm could not be computed for 7 ads.[10] All ads were matched to the college enrollment data.

A3. Sample Resumes

Four representative résumés are shown. Note that on the website used, the information here is contained in profiles rather than in the résumé format as shown. Information is redacted so as not to reveal names of firms or universities, consistent with our IRB agreement.

[10] For the 7 ads for which distance could be computed, the issue is that the street address of the firm was not provided in the ad. We were able to map these ads to CBSAs, but the geographic location was not detailed enough to measure the distance between the applicant and the firm's location.

Darius Jackson

PRESENT ADDRESS

[redacted]
Apartment #23
[redacted]

EDUCATION

[redacted]

Bachelor of Science, Economics
Graduation Date: May 2017
GPA:3.8/4.0

EXPERIENCE

Student Employee | University Dining Services [redacted] | August 2015-Present

- Responsible for serving food to students, employees, and professors.
- Opened and closed the dining hall when scheduled.
- Organized catering events for companies and future students.

Marketing Intern | [redacted] | May 2015-August 2015

- Analyzed marketing objectives, implemented marketing plans, and modeled potential improvement to company business and advertising. Reviewed the strength of competitors in local insurance industry and created potential improvements modeled off these strengths.
- Took control of the social media outlets, resulting in over 1000 unique Facebook subscribers in one month, and drastically improved online influence.
- Utilized updated marketing techniques which engaged customers more often.

Blood Drive Volunteer | [redacted] | Jan 2015-May 2015

- Assisted with greeting and registering blood donors.
- Worked with individuals, groups, and companies to recruit blood donors and promote blood drives.
- Picked up donated blood units and delivered to the laboratory to be thoroughly tested.

Skills

-SPSS Programming
-Data Analysis
-Microsoft Office
-Public Speaking
-Social Media

Xavier Washington

PRESENT ADDRESS
[redacted]

EDUCATION

[redacted]

Bachelor of Science, Psychology
Graduation Date: May 2017
GPA:4.0/4.0

EXPERIENCE

Bartender/Server [redacted] August 2015-Present

- Promoted to bartender because of work ethic.
- Quickly follow orders and complete them in a timely manner.
- Willing to jump in to help when needed.
- Handle stressful and argumentative situations with calm and pleasant demeanor.

Student Volunteer [redacted] Jan 2015-May 2015

- Mentor at-risk youth in a fast paced and high energy environment.
- Help with any activities, as specified by the program director.
- Provide an engaging, positive environment to enhance learning.

Skills

- SAS Programming
-Data Analysis
-Microsoft Office
-Public Speaking
-Social Media

Wyatt Schmidt

PRESENT ADDRESS
1122 University Ave.
[redacted]

EDUCATION

[redacted]

Bachelor of Science, Psychology
Graduation Date: May 2017
GPA:3.0/4.0

EXPERIENCE

Sales Representative [redacted] August 2015-Present

- Sold Cutco kitchen products directly to clientele, with commission as an incentive.
- Recruited client base and organized sales presentations.
- Developed public speaking and customer-client relations skills. - Developed sales and accounting experience

Research Intern [redacted] May 2015-August 2015

- Conducted experiments under the guidance of head researcher and collected necessary information for statistical analysis.
- Performed data entry to prepare databases on scientific experiments and evidence for future references.
- Made observations, recorded results, drew inferences about experiments and wrote reports on my conclusions.

Blood Drive Volunteer [redacted] Jan 2015-May 2015

- Assisted with greeting and registering blood donors.
- Worked with individuals, groups, and companies to recruit blood donors and promote blood drives.
- Picked up donated blood units and delivered to the laboratory to be thoroughly tested.

Skills

- R Programming
-Data Analysis
-Microsoft Office
-Public Speaking
-Social Media

Colin Johansson

PRESENT ADDRESS
[redacted]
Apartment #25
[redacted]

EDUCATION

[redacted]

Bachelor of Science, Business Administration
Graduation Date: May 2017
GPA:3.2/4.0

EXPERIENCE

Intramural Sports Staff Assistant [redacted] August 2015-Present

- Supervised, coached, and counseled staff of 82 officials for officiate various athletic games.
- Demonstrated leadership by evaluating officials on a nightly basis and providing them with recommendations for improvement.
- iii. Addressed and resolved customer complaints with a calm and fair approach, using both diplomacy and empathy.

Student Volunteer [redacted] Jan 2015-May 2015

- Mentor at-risk youth in a fast paced and high energy environment.
- Help with any activities, as specified by the program director.
- Provide an engaging, positive environment to enhance learning.

Skills

- SAS Programming
-Data Analysis
-Microsoft Office
-Public Speaking
-Social Media