THE DEMAND FOR INTERNS

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ABSTRACT

We first describe the demand for interns by constructing a rich data set from all available ads on a popular internship website. We find that internships which are full-time, as are most regular jobs held by college graduates, are more likely to be paid. With a machine learning algorithm, we are also able to characterize the occupation that best matches the advertised internship. We find that internships which more closely match a specific occupation are more likely to be paid. We also match each internship ad to its local labor market and find in loose labor markets internships are more likely to be unpaid. Minimum-wage increases are associated with fewer paid internships. We then conduct an audit study with more than 11,500 résumés, where we randomly assign student characteristics and apply to internships. We find that employers are more likely to respond to an application when they are looking for an unpaid intern. We find little effect of major field of study, volunteer experience, and college work experience on employer callbacks and some evidence that a higher GPA and previous internship experience increases positive employer responses. Black applicants receive fewer positive responses than white applicants, but this is entirely driven by greater discrimination against black-named applicants living far away from employers.

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Internships often provide students' first experiences in the skilled labor market. In 2015, more than 60 percent of graduates had held an internship at some point during their college careers, more than double the rate in the 1980s.[1] In response to increasing mismatch between educational attainment and jobs for new college graduates since the early-2000s (Abel, Deitz, and Su 2014) and the prioritization of relevant experience in hiring decisions (Finch, et al. 2013; Cappelli 2014; Nunley, et al. 2016; Nunley, et al. 2017), students have come under increasing pressure to obtain relevant work experience, and internships seemingly offer students a way to enhance their résumés. Empirical evidence on the labor-market returns to internship experience indicates improved early-career employment prospects (Nunley, et al. 2016) and higher earnings later in life (Saniter and Siedler 2014).

The U.S. Department of Labor (DOL) characterizes internships as a means to "provide short-term, practical experience for students, recent graduates, and people changing careers."[2] Although the durations of internships are usually less than one year and apprenticeships can last many years, internships have assumed many of the features of apprenticeships as the size of the internship market has grown. For example, a 2015 survey of U.S. firms indicates that 90 percent of interns who return for a subsequent internship are offered full-time employment.[3] Among the 90 percent offered full-time employment, almost 90 percent of them accept the offers. The high rate of transition from intern to full-time employee seems to indicate that an internship, like an apprenticeship, serves an important role in determining eventual employment.[4]

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[1] See http://www.naceweb.org/s10072015/internship-co-op-student-survey.aspx (last seen 19 March 2017) and the Lindquist-Endicott Report (1992).

[2] See https://www.bls.gov/careeroutlook/2006/summer/art02.pdf (last seen 19 March 2017).

[3] The National Association of Colleges and Employers' 2015 Internship & Co-op Survey.

[4] Fersterer, Pischke, and Winter-Ebmer (2008) find annual earnings returns to apprenticeships in Austria of approximately four percent, and also note that there is substantial heterogeneity in quality across industries and

Another institutional feature of apprenticeships—not paying a wage for the apprentice's work—has also become a common, if controversial, feature of the internship market.[5] The DOL has stated that it is possible for an intern not to be considered an "employee" under the Fair Labor Standards Act (FLSA) if the internship is similar to training obtained in an educational environment and it is understood the intern is not entitled to pay or regular employment with the firm in the future.[6] Whether interns are employees has been the subject of a federal lawsuit, in which the court ruled interns were employees and therefore subject to the FLSA (Glatt v. Fox Searchlight Pictures, Inc. 2015). But that ruling was later vacated by a federal appeals court (Glatt v. Fox Searchlight Pictures, Inc. 2016).[7]

The fundamental policy issue is whether interns should be extended the normal contractual benefits of employment. Thus, an important aspect of internships is the extent to which they resemble regular jobs. If unpaid internships maintain most or all of the characteristics of otherwise paid labor, a case could be made for the government to require firms to recognize interns as employees, who would then possess all of the attendant protections under the law. However, if unpaid internships noticeably differ from otherwise paid labor, then shoehorning internships into the legal category of paid labor would likely lower the availability of internships, which provide experience to young workers and possibly marketable job skills. Even in situations in which the

occupations in apprenticeships. Saniter and Siedler (2015) find positive wage returns of roughly six percent associated with internships. Heterogeneity in the return on internships depends, however, on the strength of labor market orientation for specific majors.

[5] Apprenticing under the supervision of a more experienced artisan for little or no pay is an ancient practice (Wallis 2008). The contracts often included bonding schemes, by which an apprentice might post a cash amount to compensate the master in the event the apprentice quits before the term is over (Elbaum 1989).

[6] See https://www.dol.gov/whd/regs/compliance/whdfs71.pdf (last seen 19 March 2017).

[7] The federal appeals court decision created a new set of criteria to determine whether the unpaid intern is the "primary beneficiary" of the internship (Glatt v. Fox Searchlight Pictures, Inc. 2016), in which case the intern would not be entitled to compensation. However, Hacker (2016) argues that the criteria generates an ambiguous test for employee status.

internship closely resembles a job, the prospect of better employment opportunities in the future may result in a greater willingness on the part of the intern to work for a zero wage.

To shed light upon the primary and surrounding policy issues regarding internships, we construct a rich data set from information contained in advertisements posted on a prominent online job/internship website to describe the demand side of the internship market. We also conduct the first large-scale résumé audit of the market for internships to estimate the effects of internship and applicant characteristics on employer responses.

The regular labor market college graduates enter and the internship market have conspicuous differences. According to the American Community Survey (ACS), 89 percent of college-educated, 24-28 year-old workers are employed full time in paid jobs, yet our data indicate that 70 percent of internships are part time and 60 percent are unpaid (Table 1). Moreover, 72 percent of full-time internships are paid, whereas only about 27 percent of part-time internships are paid. Hence, the internships that correspond time-wise with regular jobs are likely to be remunerative.[8]

To further study the characteristics of internships, the title, description, duties, responsibilities and requirements, from the advertisements, are used as inputs in a machine-learning algorithm (MLA) that (a) classifies the ads into occupation categories by assigning O*NET Standard Occupational Classification (SOC) codes and (b) assigns an occupation-match score that proxies for how closely an ad matches the characteristics of a given detailed occupation category. Although all occupation categories are represented in our sample, internships are disproportionately concentrated in the following occupation categories: (i) management, (ii) business and finance,

[8] The Pearson x^2 test for independence rejects the null hypothesis of independence between paid/unpaid and part-time/full-time statuses at the one-percent level, an indication that paid/unpaid and part-time/full-time statuses are, to some extent, jointly determined.

(iii) computer and mathematical, (iv) community and social service, (v) arts, design, entertainment, sports and media, (vi) sales, and (vii) office and administration. In most occupation categories, less than half of the internships are paid. Exceptions include architecture and engineering, sales and construction and extraction occupations. All but the sales occupation category consist of a majority of part-time internships.

The occupation-match score generates a more nuanced picture of the differences between internships and jobs. An internship assigned a high score is more closely related to the detailed occupation to which it is assigned. Thus, the occupation-match score provides a useful metric for the extent to which an internship resembles an actual job. In our data, the occupation-match scores assigned to the ads vary substantially both within and between detailed occupations.

We examine the relationship between the probability an internship is paid and the occupation-match score assigned to the ad (Figure 1).[9] The nonlinear but generally upward-sloping relationship between the two variables suggests the following: when internships resemble jobs, firms tend to pay and when the internships are relatively less job-like, firms have a tendency to offer a zero wage. The reliability of the relationship between these two variables is bolstered by our econometric analysis, which indicates that internships assigned high occupation-match scores are 20-25 percent more likely to be paid than internships assigned low scores.

Using the approach to measure "skill demands" advanced by Deming and Kahn (forthcoming), we find social, customer service, people management, and general computer skills are demanded in half or more of the ads, while cognitive and writing skills are demanded in about

[9] In Figure 1, we use a bandwidth of 0.5. In Appendix Figure 1A, we present analogous figures using different bandwidths (0.10, 0.25, 0.40, 0.60, 0.75, and 0.90). Qualitatively similar patterns are present, independent of the chosen bandwidth.

one-third of the ads.[10] Firms are less likely to pay interns when they demand cognitive or writing skills, and they are more likely to pay interns when they demand social and customer-service skills.

The geographic location of firms allows us to link internship openings to metropolitan statistical areas (MSAs) and states, which enables the of study the relationship between paid status, local-labor-market conditions, and varying minimum-wage requirements across states. We find that a one-percent increase in the MSA-level unemployment rate lowers the probability an internship is paid by about 7-9 percent. The probability an internship is paid is about six percent lower in states with a minimum wage one dollar above the level mandated by federal law. However, the overall negative relationship between minimum-wage increases and paid status is primarily concentrated among full-time internships. Moreover, there is a strong negative interaction effect between minimum-wage increases and commitments to raise the minimum wage in the future, particularly for full-time internships.

The résumé audit reveals a number of noteworthy findings. Unpaid internships have higher positive employer response rates than paid internships, suggesting that firms may need to cast a wider net to fill unpaid internships. However, the estimated response gap between paid and unpaid internships declines considerably for internships that correspond to high-paying occupations. In other words, it is similarly difficult to obtain an internship that corresponds to a high-paying occupation, independent of whether the internship is paid or unpaid. Part-time internships carry lower response rates than full-time internships, but the overall difference in response rates is driven

[10] We refer to these variables as "skill demands", which corresponds to the terminology used in Deming and Kahn (forthcoming). However, using their terminology may not be the appropriate for internships. We note that interns are expected to learn on the job and, as a result, the skills "demanded" may instead represent skills "supplied" to the interns. Firms seeking interns may also include particular words and phrases in the ads to attract the best candidates. Perhaps college students seeking internships are willing to sell their labor for a zero wage in exchange for the opportunity to develop or the ability to advertise skills valued to employers in the regular labor market.

entirely by much lower response rates for paid internships. We tend to find no effects for major field of study, volunteer experience, and college work experience. We find limited statistical evidence that having a high grade point average (GPA) or working as an intern in the past improves internship opportunities.

The only résumé attributes that have robust effects on employer responses are race and distance from employers. Black applicants receive approximately 27 percent fewer positive responses than their white counterparts. Relative to applicants residing within 250 miles of the employer, the response rate is 40 and 50 percent lower for applicants residing 500-1000 miles and 1000 miles or more away from employers, respectively. The data support statistical discrimination as the likely explanation for the racial gap in internship opportunities, as the overall difference is driven by greater racial discrimination for applicants living 500 or more miles away from employers. This finding is supported by an analysis of the text from employer responses in which black-named candidates are more likely to receive a request for information concerning their current location. These findings point toward statistical discrimination as the underlying mechanism for racial differences and contest the idea that the discrimination identified is based on implicit biases (See Bertand, Chugh and Mullainathan 2005). We also find that racial discrimination is present among applicants with low GPAs but non-existent for applicants with higher GPAs, which buttresses the statistical-discrimination interpretation.

I. Characterizing the Demand for Interns

To characterize the demand for interns, we use data from internship ads posted on a prominent

website.[11] The initial data set included 43,319 internship ads posted between fall 2016 and spring 2017.[12] The ads include whether the internship is paid, full or part time, as well as the internship title, descriptions of duties, responsibilities and requirements, the firm's geographic location, the month, day and year the ad was posted online, application deadline, and the advertising firm's name. We use this detailed information to classify internships into occupation categories as well as link the ad data to external data sources at the metropolitan-area (i.e. MSA) and occupation levels. After classifying the ads and linking them to the external data sources, the data set used in the descriptive statistics and regression analysis includes 36,882 observations with complete records.[13]

Advertisement Text

We follow Deming and Kahn (2017; DK, henceforth) by identifying particular words and phrases used in the ads that are indicative of a demand for a particular skill or attribute. Indicator variables for 10 different types of skills/attributes are created: cognitive, social, character, writing, customer service, project management, people management, financial, computer (general), and software (specific).[14] In Table 2, sample means and standard deviations are presented for the variables that proxy for firm-level demands. The internships in our sample disproportionately indicate interest in the following three attributes: social skills, customer service, and general

[11] Per our Institutional Review Board (IRB) agreement, we are unable to disclose the name of the website or the names of firms seeking interns, as we also audit firms that post advertisements on the same website.

[12] We use all internship advertisements posted on the website on 14 November 2016 and 18 March 2017. Approximately 44 percent of ads were duplicates, i.e. posted on the website at both points in time.

[13] The details associated with the sample construction, data sources, and other pertinent information about the data are provided in Appendix Section A1.

[14] See Appendix Table A1, which is a recreation of Table 1 from Deming and Kahn (forthcoming), for the words/phrases used to create variables measuring the demand for particular skills and attributes.

computer skills. Social skills, customer service and people-management skills tend to be associated with internships that are either full time, paid or both, whereas writing ability tends to be associated with internships that are either part time, unpaid or both.

Occupational Classification, Geography, On-the-Job Training, and Expected Earnings

We use the O*NET-SOC AutoCoder, a proprietary machine-learning algorithm, to assign an 8-digit O*NET-SOC code (henceforth, SOC code) to the internship ads.[15] The machine-learning algorithm relies on the information contained in the internship title and its description, responsibilities and requirements to assign the SOC codes. Obtaining a detailed SOC code allows us to examine the prevalence of internships assigned to each major occupation category as well as examine the characteristics of internships by occupation categories.

The majority of internships are assigned disproportionately to seven major occupation categories: (i) management, (ii) business and finance, (iii) computer and mathematical, (iv) community and social services, (v) arts, design, entertainment, sports and media, (vi) sales, and (vii) office and administration (Table 3). The same internship-occupation categories also represent the largest shares of internships in subsamples based on different internship statuses: paid (column 2), unpaid (column 3), part time (column 4), and full time (column 5). In the majority of occupation categories, the internships tend to be unpaid (column 6). But there are exceptions, as sales,

[15] The O*NET-SOC AutoCoder designed specifically to classify job ads into occupation categories. It is accessible via the following website: http://www.onetsocautocoder.com/plus/onetmatch (last seen 19 March 2017). For details on the O*NET-SOC AutoCoder, click on the FAQ tab, which provides information on the uses, accuracy, and methodology. 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. Javed et al. (2015) notes that CareerBuilder, a large online job board, 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 for their proprietary algorithm Carotene.

architecture and engineering, and construction and extraction internships are more likely to be paid. Part-time internships are the norm, except those belonging to the sales category (column 7).

We link the internship ads to metropolitan statistical areas (MSAs) via the geographic locations of the advertising firms. We examine the availability of internships in general as well as paid and unpaid internships across MSAs. Moreover, the precise date the ad was posted online and the MSA in which the advertising firm is located allows us to incorporate MSA-level unemployment rate for the month and year in which the ads were published online. Internships are available throughout most of the U.S., but they are more prevalent in large metropolitan areas along the coasts and in the upper Midwest (Figure 2).[16] The five MSAs with the highest number of internships per capita include a major city (i.e. New York City, Los Angeles, Atlanta, Miami, and Chicago).

After assigning SOC codes to the internship ads, we link the ads to occupation-level data from the American Community Survey (ACS) and O*NET via the SOC codes. To construct a measure of expected earnings, we compute weekly real earnings for each detailed occupation category using four years of pooled cross-section data (2012-2015) from the ACS. The measure is based on a sample of people between 24- and 28-years-old with Bachelor's degrees working full time. In our analysis, we convert the continuous measure of real earnings to an indicator variable for whether workers in detailed occupation assigned to the internship ad earn, on average, $1,000 or more per week.

We use the on-the-job training (OJT) variables available from O*NET, which consists of nine

[16] The drawback of examining internship availability at the MSA level, relative to the state level, is that population data by age are unavailable. In Appendix Figure A2, we present the number of internships per 100,000 in the population who are between 18-24 years-old in each state. We observe internship openings in all 50 states, but they are more prevalent in the mid-Atlantic states, California and Georgia. Paid internships are more common in Utah, Vermont and Montana, while unpaid internships are more common New Jersey, New York and California.

different categories of required training (e.g., none, less than one month, one to three months, three to six months, six months to one year, one year to two years, two years to four years, four to 10 years, and over 10 years), to create a measure of required OJT measured at the occupation level. For each category, O*NET reports the percentage of respondents that report a particular amount of required training. Based on this information, we construct a continuous measure of OJT. In particular, we use the midpoint in the range (e.g., two months for the one to three months category, 36 months for the two to four years category), and then multiply the midpoint in each OJT category by the percentage of respondents claiming that a particular amount (or range) of training is required for the occupation. After creating the continuous measure of OJT, we create three indicator variables to capture the impact of OJT on paid status: six months or less, six months to one year, and one year or more.[17]

Differences between Internships and Jobs

The two most glaring differences between internships and jobs are the following: the vast majority of internships are unpaid and/or part time. It is the opposite for jobs, particularly for young, college-educated workers. But they also differ in terms of other characteristics. A comparison of the summary statistics from our sample and the sample of job ads examined in DK reveals differences but also similarities between internships and jobs. Relative to the job ads examined by DK, the advertising firms in our sample tend to demand less cognitive skills, more

[17] Appendix Table A2 presents summary statistics (sample means and standard deviations) for each of the firm-level skill demands and internship characteristics measured at the occupation level overall and for selected major (2-Digit) SOC codes. The firm-level, skill-demand variables vary within and between major occupation categories. The same is true for the occupation-level characteristics assigned to the ads, except there are cases in which there is little to no variation within a particular major occupation category.

social skills, more writing skills, more ability to interact with customers, less ability to manage projects, more people-management skills, more general computer skills and less specific computer skills. The attributes, character and financial knowledge, are similarly demanded in both the internship sample and the sample of job ads used in DK's study.

We use the occupation-match score produced by the O*NET-SOC AutoCoder as a metric of how well an internship ad aligns with the characteristics of a detailed occupation. When the occupation-match score is high, the ad matches a particular detailed occupation well, and a low score indicates less overlap between the ad and the detailed occupation. Figure 3 plots the kernel density estimate for the occupation-match score for all ads.[18] From the plot, the scores range from low (50s and 60s) to high (80s and 90s) values overall and in the particular major occupation categories. Thus, a more nuanced picture regarding the extent to which internships resemble jobs emerges. In particular, it appears the degree of similarity between the two is a matter of degree, rather than either-or. Put differently, around 10 percent of ads are assigned scores that equal 90 or above. It is also the case that around 15 percent of ads are assigned scores less than 60. Thus, there is wide variation regarding the extent to which the ads correspond to the characteristics of detailed occupations, implying that our sample consists of internships that closely resemble actual jobs and others that resemble jobs to a lesser extent.

II. Determinants of Paid Status

[18] We present plots of kernel density estimates for the occupation-match score for each major occupation category (i.e. 2-digit SOC codes) in Appendix Figure A3. It is clear that differences in the occupation-match-score variable exist both within and between major occupation categories. As such, when examining the impact of the occupation-match score on internship characteristics, such as paid status, a useful sensitivity check would be to estimate the relationship using both between- and within-occupation comparisons.

Because of the controversy over unpaid internships an analysis of the determinants of paid status is particularly important for policy. We estimate models of paid status with variables measured at the ad, occupation and MSA levels. The regression model is

$$paid_{j,o,l,d} = \alpha + Z_j^{I\prime}\beta + \gamma score_{j,o} + Z_o^{II\prime}\gamma + \varphi_{\tilde{o}} + \varphi_l + \delta unemp_{l,d} + \varepsilon_{j,o,l,d}. \quad (1)$$

The terms *j*, *o*, *l*, and *d* index ads, occupation categories, metropolitan areas, the month-year the ad was posted online, respectively. The variable $paid$ equals one when an internship is paid and zero otherwise; Z_j^I is a vector of ad-specific explanatory variables, including an indicator variable for part-time status, a set of dichotomous variables that proxy for other attributes and skills demanded by advertising firms (See Deming and Kahn forthcoming), an indicator variable for ads retrieved in the fall, and an indicator variable for whether the ad was extracted in both the fall and spring data;[19] $score_{j,o}$ represents two indicator variables, one indicating occupation-match scores between 60 and 90 and another occupation-match scores of 90 and above; Z_j^{II} is a vector of occupation-level variables, which include dummy variables for different amounts of OJT required (defined in Section I) and whether the workers employed in the detailed occupation category assigned to the ad earn $1,000 or more per week; $\varphi_{\tilde{o}}$ represents occupation fixed effects (2-digit SOC level);[20] φ_l represents MSA fixed effects; $unemp_{l,d}$ is the unemployment rate for the MSA in which the advertising firm is located;[21] and ε represents factors not accounted for in

[19] Slightly more than 40 percent of the ads were posted on the website in the fall and spring when the ads were retrieved from the website.

[20] It is not possible to hold constant detailed SOC fixed effects when Z_o^{II} is included in equation (1). However, in sensitivity checks, holding constant 6-digit SOC fixed effects constant does not materially affect the estimated effects of the variables Z_j^I, $score_{j,o}$ and $unemp_{l,d}$ on paid status.

[21] In Appendix Figure A4, we display the average unemployment rate (2012-2016) for each MSA (Panel A) and the percentage change in unemployment rates for each MSA between 2012-2013 and 2015-2016 (Panel B). The maps indicate significant variation in unemployment rates both within and between MSAs.

equation (1). The α, β, γ, and δ are parameters to be estimated. We compute cluster-robust standard errors with two-way clustering on MSAs and occupations, given the non-nested nature of occupations and MSAs (See Cameron, Gelbach and Miller 2011). Because of the large number of right-hand-side variables, we present the estimated parameters in equation (1) in two different tables: Tables 4A and 4B.

From Table 4A, part-time status is strongly, negatively related to paid status. Although the magnitude of the relationship depends on the inclusion of occupation and MSA fixed effects, the size of the estimated relationship is economically and statistically significant in all specifications. Relative to full-time internships, part-time internships are between 78-87 percent less likely to be paid. Four skill demands are robust predictors of paid status across all specifications and subsamples: cognitive, social, writing, and customer-service skills. Ads that use words indicative of a demand for cognitive skills are 6-9 percent less likely to be paid, whereas those that demand social skills are 12-14 percent more likely to be paid. When examining part-time (columns 4 and 5) and full-time (columns 6 and 7) statuses, the negative relationship found for cognitive skills and the positive relationship for social skills are driven by larger even larger differences when the internships are full time.[22] Internships indicating a demand for writing skills are 14-20 percent less likely to be paid, and those that demand customer-service skills are 25-35 percent more likely to be paid. For the remaining skill demands, the parameter estimates are generally not statistically different from zero, although there are a few exceptions. Ad posted in the fall are less likely to be

[22] Following Deming (2017), we also estimate a model that includes an interaction term between the indicator variables for cognitive and social skills. We find no statistical evidence of such an interaction effect. In fact, we find the relationship between social skills and paid status is stronger when such skills *are not* coupled with cognitive skills. The estimated effects of cognitive and social skills as well as an interaction between the two variables are presented in Appendix Table A3.

paid, but the estimated relationship is not statistically significant at conventional levels. However, identical ads observed in both the spring and fall data sets, which we refer to as duplicate ads, are less likely to be paid.

In Table 4B, the indicator variables capturing medium (60 to 90) and high (90 and above) occupation-match scores are positively related to paid status. For the full sample, internships assigned occupation-match scores between 60 and 90 are between 12-14 percent more likely to be paid, while those assigned occupation-match scores of 90 and above are 20-25 more likely to be paid. The overall relationship between the occupation-match scores and paid status is driven by larger differentials for full-time internships, although the magnitude of the estimated relationship remains practically large for part-time internships.[23]

High and low levels of OJT are negatively related to paid status, but the estimated relationship is generally not statistically significant and effect sizes are small. Expected earnings, which is measured by an indicator variable for whether the average weekly earnings in the corresponding detailed occupation category is $1000 or more, is positively related to paid status. But the estimated relationship is only statistically significant when the estimates are based on between-occupation variation. The magnitude of the relationship falls sharply when major-occupation fixed effects are held constant, rending the relationship statistically significant. These patterns in the data hold for both part- and full-time internships. The unemployment rate in the regular MSA labor market negatively affects the probability an internship is paid in all specifications. However, it is only statistically significant when the full sample and the subsample of full-time internships are

[23] The weaker statistical relationship between the occupation-match scores between 60 and 90 and paid status appears to stem from a small sample size, as the economic relationship, evaluated at the mean of the dependent variable for the part- and full-time subsamples, is larger for part-time internships than it is for full-time internships (32 versus 16 percent higher probability of paid status).

considered. For the full sample of internships, the estimated relationship implies that a one-percent increase in the unemployment rate reduces the probability an internship is paid by 7-9 percent.

The next specification of interest examines the correlation between paid status and prevailing minimum wage in place across states. In particular, we estimate

$$paid_{j,s} = \alpha + X_j'\beta + \gamma minwage_s + \delta commit_s + \theta minwage_s \times commit_s + \varepsilon_{j,s}. \qquad (2)$$

The subscript j is defined above and the subscript s indexes states. The variables $paid_{j,s}$ and X_j are defined above, and the variables $minwage_s$ is the prevailing minimum wage in place at the state level; $commit_s$ is a zero-one indicator variable for whether the state has committed to raising its minimum wage in the future; $minwage_s \times commit_s$ is an interaction term;[24] and $\varepsilon_{j,s}$ is the error term.[25] When estimated equation (2), we compute cluster-robust standard errors with one-way clustering on states.

In Table 5, we present estimates based on two different versions of equation (2). In the first, we set $\delta = 0$ and $\theta = 0$, and then estimate these parameters along with β in equation (2) in the second specification. For the first specification, we find a one-dollar increase in the minimum wage above the federal level is associated with a six percent lower probability that an internship is paid. When examining part- and full-time internships separately, we find a one-dollar increase in the minimum wage above the federal level is associated with a three percent lower probability of paid status for part-time internships and an eight percent lower probability of paid status for full-time internships. The second specification reveals an interesting pattern: The relationship between the

[24] State-level minimum wages as well as commitments to raise minimum wages in the future across states are taken from the following webpage: http://www.ncsl.org/research/labor-and-employment/state-minimum-wage-chart.aspx#1 (last seen 7 August 2017).

[25] Note that we exclude variables measured at the occupation and MSA level, as the inclusion of these control variables could absorb a portion of the correlation between minimum wages and paid status. Our goal is to estimate the full effect, rather than the partial effect.

minimum wage and paid status tends to be stronger in states that have committed to raising the minimum wage in the future. For all internships, a one-dollar increase in the minimum wage above the federally-mandated amount is associated with a 9-10 percent decrease in the probability of paid status. For part-time internships, a minimum wage increase coupled with a commitment to increase the minimum wage in the future is not statistically different from than that in a state with no commitment to future minimum-wage increases. However, the association between minimum-wage increases in states with a commitment to future increases is negative and strong for full-time internships, indicating a 22 percent lower probability of paid status. Thus, the evidence using cross-state variation suggests that both minimum wage increases and commitments to future minimum-wage increases may bind on full-time internships, which tend to be more job-like, to a greater extent.

III. Resume Audit of the Internship Market

Experimental Design

Our experiment follows the traditional correspondence audit framework, which has been used to examine employment discrimination on the basis of race (Bertrand and Mullainathan, 2004; Nunley et al. 2015), age (Lahey 2008; Neumark, Burn and Button, 2015), disability status (Ameri et al. 2015), and country of origin (Oreopoulos 2011).[26] Recently, correspondence audits have been used to study the impact of traditional labor-market variables, such as unemployment duration (Farber, Silverman and von Wachter 2017; Kroft, Lange and Notowidigdo 2013; Nunley et al. 2017), quality of post-graduation employment (Farber, Silverman and von Wachter 2017;

[26] See Pager (2007), Bertrand and Duflo (2016) and Neumark and Rich (2016) for recent surveys of the audit literature.

Nunley et al. 2017), college type (i.e. for-profit versus nonprofit) (Darolia et al. 2015), and college majors and specific college programs (Deming et al. 2014; Nunley et al. 2016).

We submitted fictitious résumés to internship openings during the fall and spring semesters of the 2015-2016 academic year via a widely-used online internship search board.[27] Unlike traditional audit studies, we created online profiles for the fictive applicants, which were then reused during the semester in which resumes were submitted to internship postings.[28] Each profile was used to apply to 10 different internships and, as a result, the experiment has a clustered design. We created 576 profiles in each semester, with each profile forming a unique cluster along three dimensions: (*i*) applicant name, (*ii*) major field of study, and (*iii*) university. We used two distinctively white names (Wyatt Schmidt and Colin Johannson) and two distinctively black names (Darius Jackson and Xavier Washington).[29] Each racially-distinct name was 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, for a total of 576. Our data includes 1,152 clusters because each name-

[27] Our IRBs prohibit us from revealing the names of any firms or universities used in the experiment. Likewise, we are prohibited from providing information on the website used to submit fictive résumés.

[28] Two 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).

[29] In response to the critique provided in Charles and Guryuan (2011), it is important to use 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 used the 1984 Social Security Name Database, which provides rankings on the popularity of particular first names (overall, not by race). Babies born in 1984 would be 21-years-old in 2015 – when our experiment began. We then searched for the distinctively black and white names listed in Levitt and Dubner (2005). 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. Thus, it is likely that the names chosen for our study would be perceived as common. The names, however, should signal race, particularly when combined with the racially distinct last names. The distinctively black last names are from the following website, which based its report on the 2000 Census: https://hailtoyou.wordpress.com/2010/11/24/the-blackest-surnames-in-the-usa/. The distinctively white last names are ranked in the top five of surnames in countries with large white populations (Germany and Sweden): http://worldnames.publicprofiler.org/SearchArea.aspx.

major-university cluster is assigned a different randomly-generated résumé in the fall and spring semesters.[30] Each résumé included an email address to which prospective firms could respond.

We applied to 5,760 internship advertisements in both the spring and fall semesters of the 2015-2016 academic year, giving a total of 11,520 résumés submitted. We used the program created by Lahey and Beasley (2009) to randomize other attributes included on the résumés, including grade point average (GPA), work experience while in college, past internship experience, volunteer experience, and computer skills.[31] 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).

To produce a random sample to which we could submit the fictive résumés, we followed a five-step process.

1. Randomly select an internship category (marketing, research, or business) from which to choose an internship.[32]
2. Randomly select a part-time or full-time internship.
3. Randomly select a paid or unpaid internship.
4. Randomly select the webpage the internship is to be chosen from.[33]

[30] 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).

[31] In Appendix Table A4, we present 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. A comparison of the columns indicates balance in the random assignment of the résumé attributes to the fictive applicants' résumés across the different types of internships to which applications were submitted.

[32] We chose the marketing, research and business internship categories for two reasons. First, these categories included large numbers of both paid and unpaid internships as well as part- and full-time internships consistently across cities. Second, the experimental design allows us to study mismatch in qualifications, as it is common for business-related majors (business administration, economics and marketing) to intern in business-related fields.

[33] After completing steps 1-3, 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

5. Randomly select the internship on the webpage to which a résumé would be submitted.[34]

Random selection of internship postings also generates variation in the distance the applicant is from the employer. The internship advertisements to which we sent the fictive résumés were chosen at random in labor markets that were near the university (within roughly 0-500 miles), at an intermediate distance from the university (about 750-1250 miles), or far from the university (1250-2250 miles) of the résumé in question.

After submitting a résumé to a particular internship opening, we monitored the accounts for responses from employers. In general, we identified three types of employer responses: 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 as a "positive response", which is the primary outcome variable in the analysis of employer responses.

We present summary statistics in Table 6 for the different types of employer responses, including the positive response rate (our primary dependent variable), expressions of interest, interview opportunities, and location inquiries. The employer response rates, regardless of the type of employer response, are higher for unpaid internships than they are for paid internships (columns 2 and 3). No clear pattern in terms of employer responses is present between part- and full-time internships (columns 4 and 5).

depends which page we choose the internship from.

[34] After step 4 is completed, the webpage displays 10 internship advertisements. Thus, the random number generated is between 1 and 10. For example, a "1" indicates that we will submit a résumé to the first internship advertisement displayed.

The Effects of Applicant and Ad Characteristics on Employer Responses

We estimate the impact of applicant and ad characteristics on employer responses via the following regression model:

$$positive_{i,j} = \alpha + X_i'\beta + Z_j^{I\prime}\gamma + \varepsilon_{i,j}. \quad (2)$$

The subscripts *i* and *j* index applicants and ads, respectively. The variable $positive_{i,j}$ equals one when applicant receives a positive response from an employer and zero otherwise; X_i' is a vector of applicant characteristics, including dummy variables for racially-distinct applicant names, the university where the applicant is enrolled, major field of study, grade point averages, types of work experience accumulated while the applicant is completing their degree, whether and type of volunteer experience, past internship experience, and the distance from the internship (in miles); Z_j^I is defined in Section I; $\varepsilon_{i,j}$ represents factors that affect $positive_{i,j}$ not accounted for in equation (2); and α, β and γ are parameters of interest. Cluster-robust standard errors with one-way clustering at the name-major-university-semester level are computed. Because we regress an indicator for positive employer responses on a large number of applicant and internship characteristics, we present the estimates from equation (2) in a four different tables: Tables 7A, 7B, 7C, and 7D.[35] In each table, we present five columns of estimates, which vary depending on the internship type: all internships (column 1), unpaid internships (column 2), paid internships (column 3), part-time internships (column 4), and full-time internships (column 5).[36]

[35] In Appendix Tables A5, A6, A7, and A8, we re-estimate equation (3) using the probability an applicant receives an interview request as the dependent variable. The estimates are qualitatively similar.

[36] In Appendix Tables A9, A10, A11, and A12, we re-estimate equation (3) for different subsamples based on internship type. In particular, we present the estimated effects of the applicant and ad characteristics on positive employer responses for the following types of internships: unpaid part-time internships (column 1), unpaid full-time internships (column 2), paid part-time internships (column 3), and paid full-time internships (column 4). Although statistical power is limited in these specifications, we find qualitatively similar results.

In Table 7A, we find strong evidence of racial discrimination in the internship market. Overall, black applicants are about 27 percent (1.6 percentage points) less likely to receive a positive response than their white counterparts. The percentage point difference in the positive response rate between black and white applicants is larger for unpaid internships than it is for paid internships. However, if one evaluates the percentage point differences at the mean of the dependent variable in the unpaid and paid subsamples, the magnitude, in terms of probability, is larger for paid internships than it is for unpaid internships. The probability of receiving a positive response is about 22 percent lower for blacks relative to white when applying to unpaid internships. By contrast, the analogous differential is about 33 percent when applying to paid internships. For part-time internships, black applicants' probability of receiving a positive response is 30 percent lower than it is for their white counterparts. The probability that blacks receive positive responses from employers is lower for full-time internships, but the estimated response differential is not statistically significant.

Distance from employers is also a strong predictor of positive employer responses. In general, the data support the idea that the further away an applicant resides the less likely firms are respond positively. For all internships, applicants living between 500 and 1,000 miles away from the intern employer are about 30 percent less likely to receive a positive response that applicants living within 500 miles of the employer. The effect of distance from employers is larger for applicants who reside even further away: applicants who reside 1,000 miles or more away from employers are about 40 percent less likely to receive a positive response. The effects of distance on positive responses is robust across different types of internships (see columns 2-5).

In Table 7B, we find limited statistical evidence that majors, different grade point averages

and computers affect employer responses. For the majors, the base category is Psychology. Thus, relative to psychology, the only majors that are statistically significant are Business Administration and English, although the estimated response differentials are not statistically significant for each sample. The base category for the GPA indicator variables is a GPA of 3.0 or 3.2. Relative to a 3.0/3.2 GPA, applicants with the highest GPAs (i.e. 3.8 or 4.0) are about 16 percent more likely to receive a positive response. However, the response different between applicants with high and relatively low GPAs is not statistically robust across the subsamples selected on unpaid/paid and part-/full-time statuses. We find no statistical evidence of a statistical link between different data-analysis kills and employer responses.

In Table 7C, we examine the effects of different types of work experience on employer responses, including volunteer experience, work experience while enrolled in college, and previous internship experience. For volunteer and college-work experience, we find either no or limited evidence for statistical links between these variables and employer responses. The only exception is college-work experience via campus recreation center. We find some evidence that past internship experience improves one's subsequent internship opportunities. Relative to applicants without previous internship experience, those that interned in the past are more likely to receive positive response, particularly if the applicant worked as a research or insurance intern. However, the overall positive response gap between applicants who did and did not intern previously is driven by larger response gaps for unpaid and part-time internships.

In Table 7D, we present the estimated effects of the ad characteristics on employer responses. The positive employer response rate is about 15 percent lower for applicants applying to part-time internships than it is for full-time internships. A comparison of the estimated effects of part-time

status in columns (2) and (3) indicate that the overall impact is driven by a larger response gap for paid internships. Relative to unpaid internships, applicants pursuing paid internships are about 67 percent less likely to receive positive responses. The impact of paid status is large and highly statistically significant for both part-time (column 4) and full-time (column 5) internships. In particular, the probability to receiving a positive response from a paid internship is over 60 percent lower for part-time internships and around 75 percent less likely for full-time internships. In terms of the skill-demand variables, no clear patterns emerge. For the most part, the skill-demand variables are statistically unrelated to employer responses, although there are a few exceptions depending on the sample being examined. An *F*-test for joint exclusion of the skill-demand variables support the conclusion that the ad characteristics do not materially affect employer responses overall.

Exploring the Channel through which Racial Discrimination Operates

To sort out whether the racial discrimination detected in Table 8A is driven by taste-based discrimination (Becker 1971) or statistical discrimination (Aigner and Cain 1977; Arrow 1973; Cornell and Welch 1996; Lundberg and Startz 1983; Phelps 1972), we examine the text of the employer responses and identify location inquires (Table 8) and estimate head-to-head comparisons between black and white applicants (a) living less than or 500 or more miles away from employers (Table 9, Panel A) and (b) with low (3.0 or 3.2), medium (3.4 or 3.6), or high (3.8 or 4.0) GPAs (Table 9, Panel B).[37]

[37] In the interest of brevity, we omit the estimated effects of the other applicant and ad variables. The inclusion of the interaction terms does not materially affect the estimate effects of the other variables in equation (3). These estimates are available from the authors upon request.

In Table 8, we present evidence indicating that black applicants are more likely to receive location inquiries from prospective employers than their white counterparts. When examining all internships, the probability a black applicant receives a location inquiry is almost 50 percent higher (or 0.4 percentage points) than it is for white applicants. Relative to white applicants, black applicants are about 20 percent more likely to receive a location inquiry when applying to an unpaid internship; 63 percent more likely when applying to a paid internship; 51 percent more likely when applying to a part-time internship; and 47 percent more likely when applying to a full-time internship.

The findings from Panel A of Table 9 bolster the estimates presented in Table 8, as we find greater racial discrimination when the applicants live 500 or more miles from the companies. In fact, the overall effect of racial on employer responses is driven (almost) entirely by greater discrimination for applicants living further away from the firms. For the most part, these findings hold for different types of internships. The only exception is part-time internships: the extent of racial discrimination is similar for applicants living within 500 miles and 500 miles or more form employers. In Panel B of Table 9, we find that the overall racial discrimination is concentrated among applicants with low GPAs, as we detect economically small and statistically insignificant response differentials between black and white applicants with medium and high GPAs.

While there is no definitive test for the different types of discrimination, we view these findings in the following ways. The higher propensity of employers to inquire about the black applicants' locations, the greater discriminatory behavior against black applicants residing relatively further away from the company's location, and the concentration of discrimination among applicants with relatively low GPAs is suggestive of statistical discrimination.

The Effects of Occupation and Metropolitan-Area Variables on Employer Responses

To examine the impact of occupation and metropolitan-area variables on employer responses, we augment equation (3) to include the vector Z_o^{II} and $unemp_l$ from equation (1). In particular, the regression model of interest is specified as follows:

$$positive_{i,j,o,l} = \alpha + X_i'\beta + Z_j^{I\prime}\gamma + \delta score_{j,o} + Z_o^{II\prime}\theta + \varphi_{\tilde{o}} + \rho unemp_l + \varepsilon_{i,j,o,l}. \quad (4)$$

The terms i, j, o, l and variables X_i, Z_j^I, $score_{j,o}$, Z_o^{II}, $\varphi_{\tilde{o}}$, $unemp_l$, and $\varepsilon_{i,j,o,l}$ are previously defined.[38] The α, β, γ, θ, and ρ are parameters to be estimated. We compute cluster-robust standard errors with three-way clustering on the name-major-university-semester, occupation and MSAs (See Cameron, Gelbach and Miller 2011).

In Table 10, we present the estimated effects of the following variables on employer responses: $score_{j,o}$, Z_o^{II} and $unemp_l$. The estimated effects of the applicant and ad characteristics are suppressed in the interest of brevity.[39] Relative to ads assigned low occupation-match scores (i.e. 60 or less), applicants who apply to ads scores between 60 and 90 and 90 and above are less likely to receive positive employer responses. However, the response gap is only statistically significant when comparisons are made between ads assigned high and those assigned low scores. For the full sample, applications to ads assigned high scores are about 67 percent less likely than those assigned low scores to receive positive responses. The adverse effects of the occupation-match scores on response rates is robust across part- and full-time internships. However, the occupation-match

[38] We note that the variable $unemp_l$ does not vary by posting date in the audit data set. The reason for this is the website did not start including the posting date in the ads until Spring 2016. Thus, the unemployment rates used in the analysis of the audit data are measured at two different points in time: November 2015 and March 2016.

[39] The inclusion of the occupation- and MSA-level variable does not materially affect the estimated effects of the other variables in equation (4). These estimates are available upon request from the authors.

scores only lower response rates for unpaid internships, as no statistically discernable effect is detected for paid internships. Employer responses tend to be unrelated to different amounts of OJT required at the occupation level. For applicants pursuing internships linked to occupations that, on average, earn $1,000 or more per week, employers are about 16 percent less likely to respond positively to such applications. However, the estimated effect of occupation-level earnings on response rates is only statistically significant at the 10-percent level. A comparison of the estimates in the subsamples (columns 2-5) reveals that the overall negative effect of high earnings on response rates is driven by a larger response gap for unpaid internships. The MSA-level unemployment is negatively related to response rates, but it only has a statistically significant impact for unpaid internships.

In Table 11, we investigate the impact of expected earnings on the paid-unpaid response gap presented in Table 10. For all internships as well as subsamples of part- and full-time internships, we find a larger paid-unpaid response gaps for internships assigned to detailed occupations in which workers earn, on average, less than $1,000 per week. By contrast, we either find no statistical evidence of paid-unpaid response gap (column 1 and 3) or a smaller (column 2) paid-unpaid response gap when examining internships assigned to high-earning detailed occupations. Ultimately, the estimates presented in Table 11 suggest that it is similarly difficult to obtain a paid or unpaid internship when the internships correspond to downstream occupations that are high paying, particularly for full-time internships.

IV. External Validity

A common concern in studies like ours is external validity. Fortunately, the classification of

the internship ads into occupation categories provides a novel way to assess external validity. We present several pieces of evidence. First, we use data from the American Community Survey (ACS) to determine which occupations employ the majority of young, college-educated workers. We find the seven occupation categories that comprise over 90 percent of our web-scraped sample employ about 70 percent of young workers with college degrees. Second, using again the ACS data, we demonstrate that the ads applied to in the audit are also representative of occupations in which the vast majority of young, college-degree holders work. Likewise, we show that 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. Third, we compare occupational classification of our ads to the internship classification presented by Burning Glass (need to reference this somehow), finding extensive overlap between our data and the data presented by Burning Glass.

V. Discussion and Conclusion (preliminary)

To our knowledge, this is the first study of the market for internships. By examining a large sample of internship advertisements, we find substantive differences between internships and jobs. The majority of internships are unpaid and part time, in stark contrast to the jobs held by most recent college graduates. The occupation-match score generated by the MLA indicates wide variation in how closely internship advertisements align with the characteristics of jobs, both within and between detailed occupational categories. Internships which more closely match the description of regular occupations are significantly more likely to be remunerative. Skill demand in the market for internships is also markedly different from the skill demand in the labor market documented by Deming and Kahn (forthcoming). In our data, firms seeking unpaid interns demand skills and

attributes that are more general (e.g., cognitive, writing) whereas paid internships tend to require skills more specific to a job and/or firm (e.g., social, customer service).

According to both U.S. Department of Labor and Federal Court of Appeals, unpaid internships must provide an educational experience for young workers, without the presumption of future employment at the firms. However, firms in a competitive labor market have no incentive to provide general skills, unless workers pay for the training by accepting lower wages (Becker 2008).[40] However, Acemoglu and Pischke (1998, 1999a, 1999b), using the German apprenticeship system as an example, that firms have an incentive to provide general training as long as workers are unable to capture all the rents associated with the general training because of, for example, compression in the wage structure and/or the firm has monopsony power.[41] Our results indicate, while market structure likely plays a role, the composition of tasks performed and amount of time spent at the firm by interns may be the most important determinants in whether or not a firm is willing to pay an intern.

Previous research has shown that college graduates who obtain higher-quality initial employment have greater lifecycle earnings (Oreopoulos, von Wachter and Heisz 2012). A

[40] Assume the "primary beneficiary" test applied by the Second Circuit Court can be subsumed into whether or not a firm provides general and/or industry-specific skills to an intern in exchange for the intern's work effort. Assume further that firms and workers are searching for quality matches in the labor market and that both parties can agree to some probationary period (the internship), after which regular employment would ensue. If a functioning market for loans exists for college students who are credit constrained, zero-wage internships could generate efficiency gains in this market. In a competitive labor market, workers who complete internships would then be paid their (presumably higher) marginal products. If the earnings increase for college students compensates them for working at the zero wage rate and the production of interns at least covers training costs for firms, unpaid internships are incentive compatible.

[41] Within the framework of an imperfect labor market in which the intern training/instruction practices at firms could not be perfectly observed by a third party and workers are not paid their marginal products following internships, unpaid internships could still be incentive compatible for both college students and firms (see Acemoglu and Pischke 1999). However, any efficiency arguments made on behalf of unpaid internships likely depend upon students having access to the resources to undertake unpaid training (via family support, credit markets, and/or part-time work) and the enforceability of agreements where training is promised to college students.

possible explanation for this phenomenon is that firms who hire inexperienced workers signal those workers' abilities for the labor market (Pallais 2014).[42] Internships may also allow college students to demonstrate their ability for the market through this entry-level experience. However, firms providing the initial experience have an incentive to underprovide information on workers' abilities to the market if hiring these workers is costly (Pallais 2014). Hence, if college students are unable to compensate firms by initially working for little or no pay, firms may hire fewer college-educated workers without experience, thus permanently stunting their careers (Pallais 2014).

Results from the résumé audit suggest individuals' characteristics are only weakly related to the chances of receiving positive employer interest. We do find that students with higher GPAs are somewhat more likely to receive positive employer responses, but previous internship experience counts little towards subsequent internship success.

The two résumé characteristics which are strongly (negatively) related to positive employer responses are distance from the internship and race. Applicants who live more than 500 miles away from an internship are 30-40 percent less likely to receive a positive response. These results imply students who attend universities further from the larger labor markets, particularly in the middle of the country, are at a disadvantage when entering the skilled labor market. Fictitious résumés with black-identified names are 20-30 percent less likely to receive positive responses. However, this result is largely explained by employers questioning black-identified candidates about their current location, which may have implications for the spatial mismatch among black

[42] We note that while Pallais (2014) studies a low-skilled labor market, we believe her results may generalize to young workers in college.

college graduates (Raphael 1998).

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