Unbundling the Effects of College on First-Job Search: Returns to Majors, Minors, Internships, Study Abroad, and Computer Skills *

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Abstract

We analyze the initial job-market matching of new US college graduates with a large-scale audit study conducted during 2016 and 2017, in which 36,880 résumés of college seniors were submitted to online job postings. We simulate the experience of US college students by incorporating variation in curricular and extracurricular activities. Our analysis reveals significant variation in callback rate returns to majors, with Biology and Economics majors receiving the highest rate, particularly in occupations involving high intensity of analytical and interpersonal skills. However, minors in History and Mathematics have precisely estimated zero effects on callback rates. Internship experiences that are social skills-oriented positively influence callbacks, yet this is not the case for analytical internships. Study abroad experiences enhance callback rates, predominantly in high interpersonal skill-intensive occupations. Listing both programming and data analysis skills significantly boosts callback rates. Our study thus provides a comprehensive characterization of which features of the college experience are more and less valuable during the high-stakes, first-job matching process.

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1 Introduction

We study the initial match between new US college graduates and their first job. The annual sorting between newly minted graduates and employers carries great importance for the aggregate labor market and for individual young workers for at least two reasons. First, the share of college-educated workers and the college wage premium have steadily increased over the past four decades (Autor et al., 2020), making these workers a key determinant of aggregate productivity. Second, initial labor market conditions and first-job matches meaningfully impact young workers' long-term prospects (Kahn, 2010; Oreopoulos et al., 2012; von Wachter, 2020; Arellano-Bover, 2024), making this a high stakes process from the point of view of the worker. A large literature studies returns to heterogeneous college investments in terms of major field of study (Altonji et al., 2016), yet little is known about the causal effects of majors in the US, their effect on first-job search, or about the returns to other dimensions of a college education.

We unbundle the college experience and study the demand for heterogeneous college-educated workers at the outset of their careers with a large-scale résumé audit, conducted during the spring-summer seasons of 2016 and 2017. We submitted 36,880 fictitious résumés of graduating seniors with randomly assigned résumé characteristics. The outcome of interest is whether a submitted résumé received a callback. We estimate callback returns for majors, minors, internship experience, study abroad experience, and computer skills—five dimensions which we argue capture well heterogeneity in skills acquisition during college. The fictitious résumés—representing students from twelve public flagship universities majoring in eight fields of study—were submitted to online job postings in finance, banking, insurance, marketing, sales, and customer service.

Our audit study has several strengths that allow us to shed new light on the demand for college graduates. Randomized variation in curricular and extracurricular dimensions provides a rare opportunity to estimate causal returns to these college experiences, a challenging task with observational data due to selection issues. The exclusive focus on college seniors in search of their first job allows us to tailor the study towards this particular yet important group of workers, and to do so with a large sample size. Lastly, we exploit the text from the job advertisements and assign each posting to an occupation code, enabling us to link jobs with external occupation-level data. Thanks to these links, we estimate heterogeneous callback returns as a function of how important analytic skills and interpersonal skills are for a given job. Leveraging the years passed since the résumé audits, we also estimate heterogeneous callback rates based on the *realized* wage growth trends of different occupations between 2016/17–2019/20.

Callback rates are a simple yet conceptually attractive measure to focus on. To study first-job search returns, we would ideally observe (i) the number and quality of job offers a graduate receives (choice set) and (ii) the quality of the accepted job offer (choice). In the absence of these data, callback probabilities are meaningful because they arguably map into the ideal measures. College seniors apply to many jobs, receive offers from a subset of them, and accept their preferred job among the offer set. In an environment with search frictions, the callback rate can be thought of as a proxy of the number of offers a student will receive and, as a result, also a proxy of the quality of the first job a graduate matches with.[1]

We first estimate causal callback returns to the eight majors that were randomized across our résumés: Economics, Finance, Marketing, Psychology, Biology, Chemistry, Anthropology, and Philosophy. We find that college major is an important determinant of first-job search prospects. There is meaningful variation in callback major premiums, with the highest callback majors, Biology and Economics, featuring callback rates that are about 2 pp (13 percent of the mean) greater than the lowest callback major, Philosophy. Finding such variation among a limited number of majors suggests the existence of even greater variation across *all* the majors in US higher education. Economics and Biology are especially effective in obtaining callbacks in occupations involving high intensity of analytical skills and occupations involving high intensity of interpersonal skills.

Having a Math or a History minor both have zero returns in first-job callbacks, relative to having no minor. Our null results are precise, ruling out at the 95% level callback premiums greater than 0.84 pp and 0.71 pp for History and Math, respectively. The irrelevance of minors is noteworthy because obtaining them is a costly investment for students, typically requiring about 18–25 credit hours. Our findings suggest that employers interpret the (skill or signaling) value of minors very differently compared to majors and that investing in a minor carries no benefits during the first-job match process.

We then estimate returns to two types of internship experience: "social" internships (related to sales) and "quantitative" internships (related to analyst roles). We find that social internships generate callbacks but quantitative ones do not. Callback returns relative to no internship are 1.15 pp for social internships and non-significant 0.02 pp for quantitative internships.[2] These results align with the notion of mismatch between employers' needs and college graduates' (lack of) "soft" interpersonal skills (collaboration, personal interactions with customers, working with others), rather than "hard" technical skills.[3]

Study abroad experience improves callbacks by 0.78 pp (5 percent of the mean). This premium is exclusively concentrated among occupations with high interpersonal skills intensity, where the premium reaches 1.17 pp equivalent to 8.2 percent of the callback mean. This is consistent with employers valuing the soft, "life skills" students gather during study abroad, rather than the purely academic content of the experience.

We randomly assigned résumés to one of five computer-skills categories: listing no computer skills, basic computer skills (e.g., MS Office, social media), data analysis skills (e.g., Excel, not statistical packages), programming skills (e.g., statistical packages), and *both* programming and data analysis skills. The combination of programming and data analysis skills has substantial returns, in the magnitude of 9.3 percent of the callback mean, possibly

[1]Given the strength of the labor market in 2016 and 2017, we see the job-quality interpretation of callback rates as being more relevant than an interpretation by which callback rates represent the probability of finding any job vs. not finding a job.

[2]A caveat in interpreting our results as a comprehensive measure of the value of internships is that a likely benefit is the potential to secure a full-time position with the same employer where the internship took place. Our research design would clearly miss this benefit.

[3]https://www.shrm.org/resourcesandtools/hr-topics/employee-relations/pages/employers-say-students-arent-learning-soft-skills-in-college.aspx

because they signal a greater-than-average computing sophistication. Listing basic computer skills, programming skills, or data analysis skills in isolation feature no significant returns.

Contribution to the literature. A rich literature has studied returns to heterogeneity in college investments, mostly focusing on college selectivity (e.g., Dale and Krueger, 2002; Hoekstra, 2009; Weinstein, 2022b) and major field of study (e.g., Altonji et al., 2012, 2016). Identifying *causal* returns to majors in observational data has proven challenging due to selection. Progress on identification has occurred in settings where majors feature admission cutoffs, either outside the US (Hastings et al., 2013; Kirkeboen et al., 2016) or for a specific US case study (Economics at UCSC, Bleemer and Mehta, 2022). We contribute to this literature by providing causal first-job callback returns to eight common US majors, among a sample of résumés that is representative of large numbers of US public university students. Our targeted focus on first jobs provides additional insights regarding the role of majors in the crucial initial sorting of graduates and firms. Our findings on the importance of majors for first-job search contrasts with Nunley et al. (2016), who using a résumé audit study on individuals who are three years out of college find no meaningful role for majors. This disparity suggests that majors are particularly important for the *initial* sorting between graduates and first jobs, but less so as time passes and future employers have more information on workers arising from job experience. These results also suggest that a possible mechanism through which college majors determine differences in lifecycle earnings is through the quality of the initial match.

To our knowledge, this is the first study to estimate returns to college minors, which often complement major field of study in the US. While the popular narrative sometimes assigns high value to minors,[4] there is no empirical evidence on the causal effects of minors to assess the claims due to data limitations and lack of exogenous variation in minor completion. Apart from their novelty, our null results are noteworthy given their implication that two common minors such as History and Math, which require costly investments to complete, provide little labor market value at the initial callback stage.

Our estimates of causal returns to internships, study abroad experience, and computer skills improve our current understanding on demand for these college experiences. Kessler et al. (2019) find that, among fictitious résumés for University of Pennsylvania seniors, employers value internship experience yet do not value a résumé listing technical computer skills. Our results complement these findings by estimating returns to internships and computer skills for résumés that are more broadly representative of students at flagship public universities. Relative to Nunley et al. (2016), who similarly find positive callback internship returns for workers three years out of college, we uncover an important distinction between the value of internships that are more social in nature relative to more quantitative ones.[5] The study abroad returns we uncover are of similar magnitude to those in the résumé audit

[4]See, for instance, https://www.usnews.com/education/best-colleges/what-is-a-college-minor.

[5]Using German observational data and an IV identification strategy, Margaryan et al. (2022) find positive earnings returns to internship experience.

study of Cheng and Florick (2020). However, the smaller sample size of about 900 résumés in Cheng and Florick (2020) leads them to conclude study abroad has an average zero return, while our larger sample size leads us to reject zero returns at the 5% level (adjusting for multiple hypothesis testing). Further, our findings on study abroad being particularly valuable for high interpersonal skills jobs provide new evidence on potential mechanisms.

Lastly, we add to papers studying various aspects of the first-job matching process (Kessler et al., 2019; Arellano-Bover, 2021; Weinstein, 2018, 2022a) by providing a comprehensive characterization of the labor demand for various curricular and extracurricular college experiences, showing which features of the college experience matter most for the consequential first-job matching process.[6]

2 Experimental Design

We conducted identical résumé audits from April through July in both 2016 and 2017. Using a popular internet job search board, we submitted 36,880 randomly-generated résumés to jobs that were randomly selected from a bank of jobs created by our research team. The bank of job postings are comprised of ads in the following categories: account executive, banking, customer service, finance, insurance, and marketing. Ads requiring certifications or expertise in a foreign language and those requiring company-specific applications were excluded from the job bank. We only considered jobs posted in the last seven days. By limiting the sample to six job categories, we tailor résumés to resemble those observed by recruiters in real hiring situations. We eliminate ads that require specialized training or certificates, as a typical Bachelors-degree holder would be unlikely to apply. We exclude company-specific applications, as it would be difficult to hold constant, for example, responses to open-ended questions. Only applying to ads posted in the last seven days helps ensure that firms are actively recruiting for the position. Other than being located in the US, we imposed no location restrictions for job ads.

We use the program developed by Lahey and Beasley (2009) to randomly assign résumé attributes to fictive applications. The independent randomization of the résumé attributes allows to overcome so-called "template bias" (Lahey and Beasley, 2009, 2018). After curating the bank of jobs, research assistants submitted fictive résumés to job postings randomly-selected from the bank of jobs. In total, we sent 36,880 résumés to 9,220 unique job postings.

2.1 Applicant Characteristics

Each randomly-chosen job ad was sent four résumés. Fictive applicants were assigned a name, university, and address in close proximity to the university,[7] and different features

[6] Young workers' early experiences represent a crucial and formative period. The literature reviewed in von Wachter (2020) documents long-term effects of bad initial macroeconomic conditions on earnings (Kahn, 2010; Oreopoulos et al., 2012; Altonji et al., 2016; Schwandt and von Wachter, 2019) and skill accumulation (Arellano-Bover, 2022), as well as the long-term importance of first-employer quality (Arellano-Bover, 2024). Finamor (2023) provides evidence of resulting strategic timing of college graduation.

[7] This means every applicant is assigned the same address when assigned a given university, which could, in some cases, introduce template bias. To avoid this and reduce the risk of detection, within a job ad, the four

of the college experience. Our features of interest are majors, minors, internships, study abroad, and computer skills.[8]

2.1.1 Demographics

Names were chosen to indicate race/ethnicity and gender. The White-sounding names are Colin Schneider, Jack Schwartz, Claire Haas, and Madeline Krueger; the Black-sounding names are Darius Jackson, Xavier Washington, Kiara Banks, and Jasmin Booker; and the Hispanic-sounding names are Diego Martinez, Andres Flores, Adriana Hernandez, and Gabriela Lopez. For each of the aforementioned race/ethnic groups, the first two listed are male-sounding names and the latter two are female-sounding names. Race/ethnicity were assigned with probability $1/3$ and gender was assigned with probability $1/2$. Thus, the probability of being assigned a given racial/ethnic-gender specific name is $1/6$.[9]

2.1.2 Universities, Majors, and Minors

The 12 universities chosen for the experiment are large flagship universities located in each of the five Census regions: two in the Southeast, three in the Midwest, two in the Northeast, two in the Southwest, and two in the West. Their identities cannot be disclosed per our IRB agreement. The majors we assigned to résumés are Anthropology, Biology, Chemistry, Economics, Finance, Marketing, Philosophy, and Psychology. The universities and majors were assigned with equal probability: $1/12$ for the universities and $1/8$ for the majors. Half of applicants were assigned a minor. Conditional on being assigned a minor, History and Mathematics were assigned with equal probability.

The majors were selected based on two considerations. The first is the overall representativeness of the majors in the college-education population. According the 2016–2017 American Community Surveys (ACS), the eight majors chosen for our experiment are held by 20.5 percent of 21-26 year-old college graduates. Among 21–26 year-old college graduates who are employed, the share of the majors employed in the occupations linked to the audited ads is higher (21.5 percent) than it is for occupations not represented in the audit (17.4 percent). The second is our interest in expanding the breadth of majors, including majors that are disproportionately found in the audit occupations (Anthropology, Economics, Finance, and Marketing), those that are underrepresented in audit occupations (Biology and Chemistry), and those that are employed in audit and non-audit occupations at similar rates (Psychology and Philosophy). We verified that all of these majors were offered at each of the 12 public universities included in the study.

Our goal for the minors was to include one that required writing/reading skills and the other that emphasized problem solving. Although the majority of majors are offered

submitted résumés always featured four different universities.

[8] We additionally included other features typically listed in résumés. In Table A1, we present each of the randomly assigned résumé characteristics, the probabilities chosen for the assignment of each attribute, and summary statistics.

[9] In ongoing work, Bushnell et al. (2024) use data from this same audit study to quantify racial discrimination in hiring.

at most flagship universities, minor offerings across universities is less consistent. After selecting the 12 universities, we examined their minor programs. History and Mathematics were two of the minors offered at each of the 12 universities. To our knowledge there is no nationally representative data on minors and their prevalence among college students' academic choices.

2.1.3 Internship Experience

We characterize randomly assigned internships as either "quantitative" or "social" in nature. A "social" internship might involve a sales role, whereas an analyst or research role would be "quantitative".[10]

2.1.4 Study Abroad Experience

We assigned study abroad experience to 25 percent of applicants. The countries to which the study abroad scholarships are linked include Argentina, China, Dubai, Italy, Japan, Mexico, and South Africa. Thus, the probability of an applicant being assigned a study abroad scholarship in any one of the aforementioned countries is $1/28$. Our empirical analyses collapse the study abroad scholarships by country into a single category, which captures the average effect of any study abroad experience.

2.1.5 Computer Skills

Résumés either indicated no computer skills (25 percent), basic computer skills (e.g., MS Office and social media; 25 percent), ability to conduct data analysis (e.g., Excel; 25 percent), the ability to program in different languages (e.g., statistical packages; 12.5 percent), and the ability to both conduct data analysis and program in different languages (12.5 percent).

2.1.6 Other Résumé Characteristics

Table A1 presents a comprehensive lists of additional résumé characteristics that were randomly assigned. These include GPA and language abilities, among others.

2.2 Ad Classification and External Data Sources

We used the O*NET-SOC Autocoder to assign each job ad an 8-digit O*NET-SOC code. Almost 94 percent of the applications were sent to job ads that map into one of six 2-digit SOC codes: banking and financial operations (21.2 percent), management (9.5 percent), office and administration (26.8 percent), and sales (36 percent). Figure 1 shows the occupation distribution of job posts at the 3-digit level. Sales representatives in services lead with nearly 20%, followed by information and record clerks at 14.4%, and financial specialists at 13.6%.

[10]There are a total of 60 precise internship labels we use. These can be aggregated into three quantitative internships (Marketing Analyst, Financial Analyst, General Research) and three social internships (Marketing Sales, Financial Sales, and General Sales). Our main findings on social vs. quantitative internships hold when separately analyzing these six disaggregated categories.

Retail sales workers and secretaries each make up less than 3%. The 'Other' category, which includes roles with less than 1% of postings, makes up 4.4%, indicating a wide variety of occupations in the sample.

After classifying ads into specific occupation categories, we linked them to O*NET and the ACS. We use the ACS to group occupations as a function of their realized 2016/17–2019/20 occupation-level wage growth (i.e., occupations that have experienced better vs. worse trends after résumés were sent). While the occupation classification was carried out using external ACS data, the unconditional callback rates confirm that the classification indeed captures occupations' growth. The callback rates among job postings corresponding to low- and high-growth occupations were equal to 11 and 18.7 percent, respectively.

We also link the ACS and O*NET data sets to compute analytical and interpersonal task intensities by occupation, based on the two task measures from the taxonomy provided by Acemoglu and Autor (2011). Task intensities are then used to group ads into high and low intensity bins separately for analytical and interpersonal tasks.

Appendix B presents more details on occupational classification and corresponding linkages.

2.3 Macroeconomic Environment

During the first wave of the experiment, March-July 2016, the US unemployment rate fluctuated between 4.8–5.0 percent. The range during the second, March-July 2017 wave was 4.3–4.4 percent. On average, nonfarm payrolls grew around 1.5 percent over the 2016-2017 period. Growth in real average hourly wages was 0.8 percent in 2016, and it was 0.2 percent between November 2016 and November 2017. Thus, at the time of our experiment, the labor market had tightened substantially from the height of the Great Recession, yet improvements in labor market conditions had not translated into robust real wage growth.

In short, our job applications were sent out during times of low unemployment rates and a positive macroeconomic trend. From the perspective of the graduating-in-a-recession literature, our cohorts would not be "unlucky" ones (Schwandt and von Wachter, 2019). One implication of this context for our findings is that callback rates are unlikely to capture the distinction between finding any job vs. unemployment. Rather, we interpret callback rates as a proxy for the number of first-job offers a graduating senior will receive and, as such, the (likely) quality of the chosen first job.

3 Empirical Approach

We estimate different versions of the following linear regression, representing the probability that a submitted résumé receives a callback:

$$\text{Callback}_i = \alpha + \mathbf{R}_i'\beta_1 + \psi_{j(i)} + \varepsilon_i, \tag{1}$$

where Callback_i is a dummy variable equal to one if résumé i received a callback, $\mathbf{R}_i'$ is a vector of résumé characteristics, $\psi_{j(i)}$ is a job ad fixed effect, and β_1 is the parameter vector of interest capturing the causal effect of résumé characteristics $\mathbf{R}'_i$ on the callback probability. We estimate five versions of equation (1): setting $\mathbf{R}'_i$ to include majors, minors, internships, Study Abroad experience, or computer skills.

We also estimate the following augmented version of equation (1):

$$\text{Callback}_i = \delta + \mathbf{R}'_i\beta_2 + \mathbf{X}'_i\gamma + \Phi_{u(i)} + \psi_{j(i)} + \nu_i, \tag{2}$$

where $\mathbf{X}'_i$ includes race/ethnicity (dummies for black-, Hispanic-, or white-sounding names) and gender (dummies for female- or male-sounding names) résumé covariates. The set of dummies $\Phi_{u(i)}$ represents fixed effects for each of the twelve public flagship universities u featured in the résumés.

We estimate equations (1) and (2) after multiplying the callback dummy times 100 so that returns can be interpreted in percentage terms.

Given the relatively large number of parameters we estimate, we report statistical significance based on standard p-values and on p-values that account for multiple hypothesis testing, following the procedure developed by Romano and Wolf (2005a,b, 2016).

3.1 Heterogeneity

We estimate β_1 and β_2 in the full sample and then test for heterogeneous effects when splitting the sample in three different ways, all based on the characteristics of the occupation of the job posting a résumé was submitted to.[11]

First, we divide occupations into those that experienced below- or above-median occupation-level wage growth between 2016/17–2019/20. Since our fictitious résumés were sent during Spring-Summer of 2016 and 2017, this split captures heterogeneous effects between occupations that have *ex-post* experienced better or worse wage trends.

Second, we divide occupations into those featuring below- or above-median intensity of non-routine cognitive *analytical* skills (Acemoglu and Autor, 2011). These skills are related to analyzing data, creativity, and interpreting information. We interpret this split as one related to the importance a job places on "hard" cognitive skills.

In the third split, we divide occupations into those featuring below- or above-median intensity of non-routine cognitive *interpersonal* skills (Acemoglu and Autor, 2011). These skills are related to establishing and maintaining personal relationships as well as working with/managing coworkers. We interpret this split as one related to the importance a job places on "soft" skills or social skills.

4 Results

This section presents callback returns to majors, minors, internships, study abroad, and computer skills. We present and discuss estimates of β_2. Corresponding estimates of β_1 are

[11] For all heterogeneity sample splits, we compute occupation-level characteristics using the external data sources and then compute the résumé-weighted median in our dataset. Heterogeneity splits are thus close to 50–50 in sample size.

very similar and can be found on Tables A2–A6 in Appendix A.

4.1 Majors matter

Table 1 shows estimates of β_1 and β_2 in equations (1) and (2) when $\mathbf{R}_i$ includes dummy variables for majors in Economics, Finance, Marketing, Psychology, Biology, Chemistry, and Anthropology. The omitted category is Philosophy, the major with the lowest callback rate.

Baseline. Column (1) in Table 1 shows baseline estimates of callback returns to majors. Majors matter when transforming résumé submissions into callbacks. Overall, 14.95% of résumés received a callback. This rate was 13.56% among the omitted Philosophy major. Relative to this baseline, Biology, Economics, Chemistry, and Marketing had positive and statistically significant premiums ranging from 1.05 pp for Marketing to 1.97 pp for Biology.[12] These are sizable effects, as 1.97 pp corresponds to 14.5 percent of the baseline rate. Instead, callback rates for Finance, Psychology, and Anthropology majors are indistinguishable from Philosophy. The joint test of all majors having equal returns has an (unadjusted) p-value of 0.002.

By occupation-wage growth. Columns (2) and (3) in Table 1 show callback returns to majors, separately for low vs. high wage growth occupations. Column (2) shows that major returns are generally stronger among low-growth occupations. Biology and Economics, the highest-return majors, feature returns in low-growth occupations of 2.34 and 2.32 pp, respectively (21 percent of the baseline callback). In high-growth occupations, the corresponding returns are 1.59 and 1.52 pp. This would suggest majors play a differential role especially for occupations that are hiring less, with low callback rates.

By analytical skills intensity. Columns (4) and (5) in Table 1 show callback returns to majors, separately for occupations with low and high analytical skills intensity. All majors feature greater returns among high analytical skills occupations. Biology and Economics, with 3.19 and 3.04 pp respective returns, feature the most callbacks, as in the full sample. Marketing, with modest returns in the full sample, is the third highest-ranked major for high analytical skills occupations with returns of 2.36 pp (16 percent of the mean).

By interpersonal skills intensity. Columns (6) and (7) in Table 1 show callback returns to majors, separately for occupations with low and high interpersonal skills intensity. Except for Chemistry, all majors feature greater returns among high interpersonal skills occupations. Biology and Economics, with 2.94 and 2.75 pp respective returns, feature the most callbacks, as in the full sample. As with analytical skills, Marketing performs quite well among the high interpersonal skills sample (returns of 1.82 pp) in spite of its modest full-sample returns.

[12] Returns to Marketing are not statistically significant when adjusting for multiple-hypothesis testing.

4.2 Minors' irrelevance

Table 2 shows estimates of β_2 in equation (2) when $\mathbf{R}_i$ includes two dummy variables: one for holding a History minor and one for holding a Math minor. The omitted category is holding no minor.

Baseline. Column (1) in Table 2 shows baseline estimates of callback returns to minors. The takeaway is that holding a minor has no statistically significant effects on callback rates. The no-minor omitted category has a callback rate of 14.81%. Relative to this baseline, holding a History minor has a 0.14 pp effect on callback rates (unadjusted p-value equal to 0.704). Holding a Math minor has a 0.01 pp effect on callback rates (unadjusted p-value equal to 0.988). At the 95% confidence level, we can rule out positive effects greater than 0.84 and 0.71 pp for History and Math minors, respectively.

Heterogeneity. Columns (2)–(7) in Table 2 show estimates of callback returns to History and Math minors, separately for low vs. high wage growth occupations, separately for occupations with low and high analytical skills intensity, and separately for occupations with low and high interpersonal skills intensity. Holding a minor fails to deliver statistically significant returns across all these subsamples, with null effects that are precisely estimated in all cases.

4.3 "Social" internships help, "quantitative" ones do not

Table 3 shows baseline estimates of β_2 in equation (2) when $\mathbf{R}_i$ includes two dummy variables: one for a résumé featuring a "social" internship (related to sales roles) and one for featuring a "quantitative" internship (related to analyst roles). The omitted category is listing no internship.

Baseline. Column (1) in Table 3 shows estimates of callback returns to internships. Social internships improve callback rates while quantitative internships do not. The callback rate among résumés without internship was 14.8 percent. Relative to this baseline, featuring a social internship resulted in a 1.15 pp higher callback rate, equivalent to 7.8 percent of the baseline rate. Instead, featuring a quantitative internship had a non-significant 0.02 pp effect.

By occupation-wage growth. Columns (2) and (3) in Table 3 show estimates of callback returns to internships, separately for low vs. high wage growth occupations. Quantitative internships continue to have no advantage in either subsample, with small and non-significant returns. Instead, the positive return to social internships is fairly similar across both occupation groups (1.08 and 1.22 pp).[13] In relative terms, however, the premium is greater for low-growth occupations since they feature lower baseline rates.

[13] Although returns in high-growth occupations are not significant when adjusting p-values.

By analytical skills intensity. Columns (4) and (5) in Table 3 show estimates of callback returns to internships, separately for occupations with low and high analytical skills intensity. As in the full sample, quantitative internships provide no significant returns in either subsample. Instead, the positive effects of social internships are concentrated among high analytical skills occupations (1.43 pp).

By interpersonal skills intensity. Columns (6) and (7) in Table 3 show estimates of callback returns to internships, separately for occupations with low and high interpersonal skills intensity. Quantitative internships do not have any significant returns in any of these two subsamples. Returns to a social internship are greater among high interpersonal skill occupations, with 1.34 pp return (9.5% of baseline), which is indicative of these internships providing social skills that are valued by employers. Among low interpersonal skill occupations, the return is 0.89 pp (not significant when adjusting p-values).

4.4 Study abroad helps, particularly for high-interpersonal skills jobs

Table 4 shows estimates of β_2 in equation (2) when $\mathbf{R}_i$ includes a dummy variables for a résumé featuring study-abroad experience.

Baseline. Column (1) in Table 4 shows estimates of callback returns to study abroad. The main takeaway is that study abroad improves callback rates. The callback rate among résumés that did not list study-abroad experience was 14.76. Relative to this baseline, study-abroad experience led to a callback rate that is 0.78 pp higher and statistically significant at the 5 percent level (adjusted for multiple-hypothesis testing).

By occupation-wage growth. Columns (2) and (3) in Table 4 show estimates of callback returns to study-abroad experience, separately for low vs. high wage growth occupations. Returns to study abroad are statistically significant among low-growth occupations but not among high-growth ones. The return among low-growth occupations is equal to 0.95 pp.

By analytical skills intensity. Columns (4) and (5) in Table 4 show estimates of callback returns to study abroad, separately for occupations with low and high analytical skills intensity. Returns to study abroad are concentrated in high analytical skills occupations (returns of 0.99 pp) and non-significant among low analytical skills occupations. This pattern coincides with that of returns to social internships.

By interpersonal skills intensity. Columns (6) and (7) in Table 4 show callback returns to study abroad, separately for occupations with low and high interpersonal skills intensity. Returns are concentrated on high interpersonal skills occupations, equal to 1.17 pp, which is equivalent to 8.2 percent of the callback mean. Instead, we find no evidence of callback returns for study abroad among low interpersonal skill occupations (0.32 pp, unadjusted p-

value equal to 0.48). These patterns align with the notion that employers might value study abroad for the non-cognitive, "life-experience" skills it provides.

4.5 Computer skills: Programming and data analysis combination helps

Table 5 shows estimates of β_2 in equation (2) when $\mathbf{R}_i$ includes dummies for four mutually exclusive computer skills groups: basic computer skills, data analysis skills, programming skills, and *both* programming and data analysis skills. The omitted category is listing no computer skills on the résumé.

Baseline. Columns (1) and (2) in Table 5 show estimates of callback returns to computer skills. The greatest callback premium arises from the combination of programming and data analysis skills. The callback rate among résumés not listing any computer skills was 14.46 percent. Résumés listing both programming and data analysis skills had a 1.39 pp higher callback rate, about 9.6 percent of the baseline rate. Résumés listing basic skills or programming or data analysis skills in isolation featured no statistically significantly higher callback rates. There is suggestive evidence of complementarities since the estimated return to both programming and data analysis skills is greater than the sum of the estimated returns to each skill separately.[14]

By occupation-wage growth. Columns (2) and (3) in Table 5 show callback returns to computer skills, separately for low vs. high wage growth occupations. The only return that remains significant after adjusting for multiple-hypothesis testing is the programming/data skills combination among high wage-growth occupations (1.64 pp, significant at the 10% level).

By analytical skills intensity. Columns (4) and (5) in Table 5 show callback returns to computer skills, separately for occupations with low and high analytical skills intensity. With this sample split, only the combination of data analysis and programming skills has positive and significant returns. The estimated returns are equal to 1.56 and 1.27 pp among low and high analytical skill intensity occupations, respectively (the latter is non-significant when adjusting p-values).

By interpersonal skills intensity. Columns (6) and (7) in Table 5 show callback returns to computer skills, separately for occupations with low and high interpersonal skills intensity. Only the programming and data analysis combination features positive and significant returns in the high-skill subgroup, equal to 1.61 pp. This would be suggestive of complementarities between advanced computer skills and interpersonal skills, or relative scarcity in the joint supply of these two skill sets.

[14]However, the standard errors imply we fail to reject $\beta_2^{\text{Data}} + \beta_2^{\text{Prog}} = \beta_2^{\text{Data+Prog}}$ (unadjusted p-value equal to 0.52).

5 Conclusion

In 2016–2017, we conducted a large-scale résumé audit of the labor market for newly-minted college graduates. We simulated their first-job search process by randomizing curricular and extra-curricular experiences during school.

On curricular experiences, the key takeaway is that majors matter while minors do not—not even a Math minor. The findings on majors are valuable given how the literature has struggled to document causal major returns in the US. The precisely estimated null returns to minors have important implications given (i) how these findings run against public perception and counseling guidelines and (ii) the large private investments students across the US undertake in obtaining minors.

Our findings speak to the debate on college students' (lack of) soft skills. Whereas History or Math minors provide no returns, the arguably social and life skills provided by sales internships (but not analyst internships) and study abroad experiences are rewarded in the first-job match process. Moreover, our heterogeneity analyses reveals that these soft skills are especially valued in occupations demanding high *analytical* skills, suggesting a role for complementarities and high demand for soft skills in hard-skills jobs.

Taken together, our results reflect firms place priority on more analytical majors and combinations of data and programming skills acquired in school. However, for ancillary experiences which occur outside of the university, such as internships and study abroad, firms appear to value their social, non-cognitive aspects. We qualify these results with a few observations. First, these data were collected in a historically tight labor market for college graduates and the first-job matching process could work differently during downturns (Forsythe, 2022). Second, the literature has shown that the task content of work for college graduates is rapidly changing (Deming and Noray, 2020). Hence, our study offers a small, albeit revealing, window into the first-job matching process for these two cohorts of college graduate job seekers.

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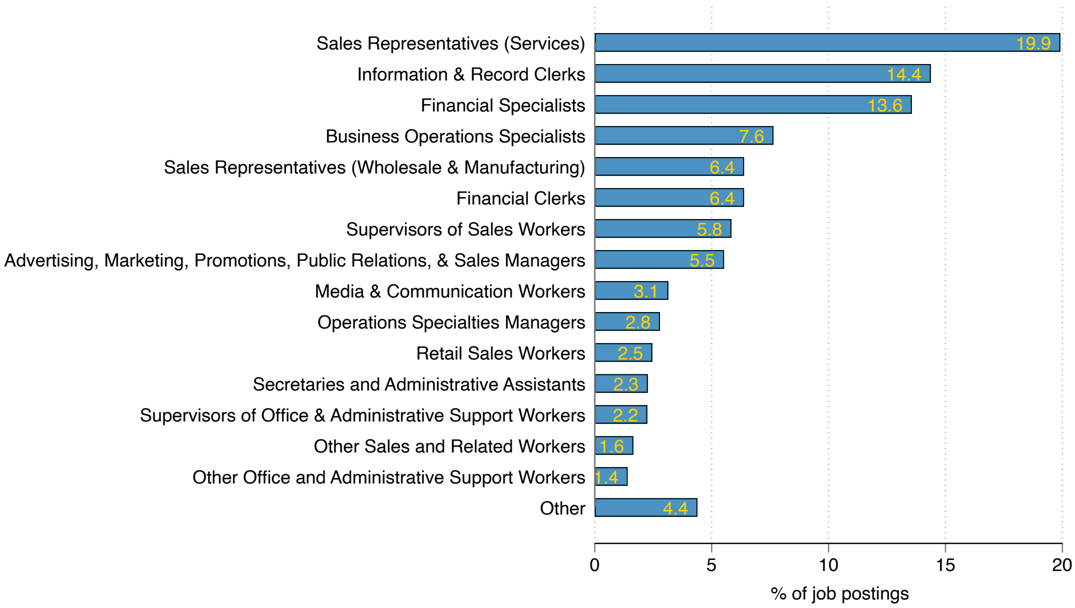
6 Figures and Tables

Figure 1: 3-digit Occupation Distribution of Job Postings



Notes: Distribution of 3-digit SOC occupations across job postings where fictive résumés were submitted. The "Other" category groups all 3-digit occupations with less than 1 percent of job postings in our sample.

Table 1: Effects of Majors on Callback Rates

	Baseline	By 2016/17–2019/20 Δ Occ. Wage		By Analytical Skills Intensity		By Interpersonal Skills Intensity	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Economics	1.90***	2.32***	1.52*	0.49	3.04***	0.88	2.75***
	(0.59)‡ ‡ ‡	(0.76)‡ ‡ ‡	(0.90)	(0.90)	(0.78)‡ ‡ ‡	(0.91)	(0.78)‡ ‡ ‡
Finance	-0.09	0.61	-0.80	-1.68*	1.21	-1.63*	1.20
	(0.60)	(0.75)	(0.93)	(0.90)	(0.79)	(0.91)	(0.79)
Marketing	1.10*	1.61**	0.57	-0.48	2.36***	0.17	1.82**
	(0.59)	(0.78)	(0.89)	(0.87)	(0.81)‡ ‡ ‡	(0.89)	(0.80)‡
Psychology	0.53	0.20	0.86	-0.80	1.58**	-0.20	1.14
	(0.58)	(0.77)	(0.87)	(0.88)	(0.77)	(0.88)	(0.77)
Biology	1.97***	2.34***	1.59*	0.47	3.19***	0.86	2.94***
	(0.60)‡ ‡ ‡	(0.76)‡ ‡ ‡	(0.92)	(0.89)	(0.81)‡ ‡ ‡	(0.90)	(0.81)‡ ‡ ‡
Chemistry	1.34**	1.05	1.65*	1.00	1.57*	1.67*	1.01
	(0.59)‡	(0.76)	(0.91)	(0.88)	(0.81)	(0.90)	(0.79)
Anthropology	0.94	0.70	1.17	-0.31	1.92**	0.12	1.62**
	(0.59)	(0.74)	(0.91)	(0.89)	(0.79)‡‡	(0.89)	(0.79)
Heterogeneity split	-	Low	High	Low	High	Low	High
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Job ad fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Callback mean	14.95	10.98	18.71	15.18	14.76	15.78	14.23
Callback mean, omitted category	13.56	10.05	16.92	15.04	12.39	15.09	12.28
Observations	36,880	17,912	18,968	16,748	20,132	17,260	19,620

Notes: Parameter estimates for callback returns to majors, estimated in equation (2). Callback dummy is multiplied by 100. Controls include university fixed effects, race/ethnicity and gender (based on first names attached to résumés). Standard errors clustered at the job ad level in parentheses. The omitted category is a major in Philosophy.

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.
(based on p-values unadjusted for multiple-hypothesis testing).

‡ ‡ ‡ Significant at the 1 percent level.
‡‡ Significant at the 5 percent level.
‡ Significant at the 10 percent level.
(based on p-values adjusted for multiple-hypothesis testing).

Table 2: Effects of Minors on Callback Rates

	Baseline	By 2016/17–2019/20 Δ Occ. Wage		By Analytical Skills Intensity		By Interpersonal Skills Intensity	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
History Minor	0.14	0.50	-0.19	-0.29	0.51	-0.00	0.31
	(0.36)	(0.44)	(0.56)	(0.53)	(0.49)	(0.55)	(0.47)
Math Minor	0.01	0.51	-0.51	0.06	-0.03	0.02	0.00
	(0.36)	(0.48)	(0.54)	(0.54)	(0.48)	(0.53)	(0.49)
Heterogeneity split	-	Low	High	Low	High	Low	High
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Job ad fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Callback mean	14.95	10.98	18.71	15.18	14.76	15.78	14.23
Callback mean, omitted category	14.81	10.85	18.57	15.18	14.50	15.61	14.11
Observations	36,880	17,912	18,968	16,748	20,132	17,260	19,620

Notes: Parameter estimates for callback returns to minors, estimated in equation (2). Callback dummy is multiplied by 100. Controls include university fixed effects, race/ethnicity and gender (based on first names attached to résumés). Standard errors clustered at the job ad level in parentheses. The omitted category is no minor.

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.
(based on p-values unadjusted for multiple-hypothesis testing).

‡ ‡ ‡ Significant at the 1 percent level.
‡‡ Significant at the 5 percent level.
‡ Significant at the 10 percent level.
(based on p-values adjusted for multiple-hypothesis testing).

Table 3: Effects of Internships on Callback Rates

	Baseline	By 2016/17–2019/20 Δ Occ. Wage		By Analytical Skills Intensity		By Interpersonal Skills Intensity	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Social Internship	1.15***	1.22***	1.08**	0.77	1.43***	0.89*	1.34***
	(0.36)‡ ‡ ‡	(0.47)‡‡	(0.53)	(0.53)	(0.48)‡ ‡ ‡	(0.54)	(0.47)‡ ‡ ‡
Quantitative Internship	0.02	-0.03	0.05	0.35	-0.25	0.31	-0.25
	(0.34)	(0.41)	(0.54)	(0.52)	(0.45)	(0.53)	(0.44)
Heterogeneity split	-	Low	High	Low	High	Low	High
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Job ad fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Callback mean	14.95	10.98	18.71	15.18	14.76	15.78	14.23
Callback mean, omitted category	14.80	10.67	18.71	14.91	14.71	15.64	14.05
Observations	36,880	17,912	18,968	16,748	20,132	17,260	19,620

Notes: Parameter estimates for callback returns to internships, estimated in equation (2). Callback dummy is multiplied by 100. Controls include university fixed effects, race/ethnicity and gender (based on first names attached to résumés). Standard errors clustered at the job ad level in parentheses. The omitted category is no internship.

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.
(based on p-values unadjusted for multiple-hypothesis testing).

‡ ‡ ‡ Significant at the 1 percent level.
‡‡ Significant at the 5 percent level.
‡ Significant at the 10 percent level.
(based on p-values adjusted for multiple-hypothesis testing).

Table 4: Effects of Study Abroad Experience on Callback Rates

	Baseline	By 2016/17–2019/20 Δ Occ. Wage		By Analytical Skills Intensity		By Interpersonal Skills Intensity	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Study Abroad	0.78***	0.95**	0.61	0.51	0.99**	0.32	1.17***
	(0.30)‡‡	(0.37)‡‡	(0.46)	(0.45)	(0.40)‡‡	(0.45)	(0.39)‡ ‡ ‡
Heterogeneity split	-	Low	High	Low	High	Low	High
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Job ad fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Callback mean	14.95	10.98	18.71	15.18	14.76	15.78	14.23
Callback mean, omitted category	14.76	10.74	18.55	15.05	14.52	15.68	13.94
Observations	36,880	17,912	18,968	16,748	20,132	17,260	19,620

Notes: Parameter estimates for callback returns to study abroad experience, estimated in equation (2). Callback dummy is multiplied by 100. Controls include university fixed effects, race/ethnicity and gender (based on first names attached to résumés). Standard errors clustered at the job ad level in parentheses. The omitted category is no study abroad experience.

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.
(based on p-values unadjusted for multiple-hypothesis testing).

‡ ‡ ‡ Significant at the 1 percent level.
‡‡ Significant at the 5 percent level.
‡ Significant at the 10 percent level.
(based on p-values adjusted for multiple-hypothesis testing).

Table 5: Effects of Computer Skills on Callback Rates

	Baseline	By 2016/17–2019/20 Δ Occ. Wage		By Analytical Skills Intensity		By Interpersonal Skills Intensity	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Basic Computer Skills	0.68*	0.27	1.06*	0.89	0.54	0.69	0.70
	(0.36)	(0.47)	(0.55)	(0.55)	(0.48)	(0.55)	(0.48)
Programming Skills	0.51	0.43	0.49	0.47	0.59	0.89	0.20
	(0.47)	(0.62)	(0.70)	(0.68)	(0.65)	(0.68)	(0.65)
Data Analysis Skills	0.42	-0.03	0.81	0.78	0.15	0.96*	-0.02
	(0.37)	(0.46)	(0.56)	(0.54)	(0.49)	(0.56)	(0.48)
Programming and Data Analysis Skills	1.39***	1.10*	1.64**	1.56**	1.27**	1.13	1.61***
	(0.47)‡ ‡ ‡	(0.58)	(0.74)‡	(0.71)‡	(0.63)	(0.72)	(0.62)‡‡
Heterogeneity split	-	Low	High	Low	High	Low	High
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Job ad fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Callback mean	14.95	10.98	18.71	15.18	14.76	15.78	14.23
Callback mean, omitted category	14.46	10.79	17.92	14.52	14.40	15.11	13.88
Observations	36,880	17,912	18,968	16,748	20,132	17,260	19,620

Notes: Parameter estimates for callback returns to computer skills, estimated in equation (2). Callback dummy is multiplied by 100. Controls include university fixed effects, race/ethnicity and gender (based on first names attached to résumés). Standard errors clustered at the job ad level in parentheses. The omitted category is listing no computer skills.

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.
(based on p-values unadjusted for multiple-hypothesis testing).

‡ ‡ ‡ Significant at the 1 percent level.
‡‡ Significant at the 5 percent level.
‡ Significant at the 10 percent level.
(based on p-values adjusted for multiple-hypothesis testing).

A Additional Tables and Figures (for online publication)

Table A1: Summary Statistics for and Probabilities Assigned to Résumé Characteristics

Résumé Characteristic	Mean/Std. Dev.	Assigned Probability	Résumé Characteristic	Mean/Std. Dev.	Assigned Probability	Résumé Characteristic	Mean/Std. Dev.	Assigned Probability
Demographic–Black	0.329 (0.470)	0.333	Major–Philosophy	0.124 (0.329)	0.125	Computer–Data Analysis	0.250 (0.433)	0.250
Demographic–Hispanic	0.336 (0.472)	0.333	Major-Chemistry	0.125 (0.330)	0.125	Computer–Basic Skills	0.250 (0.433)	0.250
Demographic–Women	0.500 (0.500)	0.500	Major-Biology	0.124 (0.329)	0.125	Language–Native Fluent	0.082 (0.275)	0.083
University–Southeast #1	0.082 (0.275)	0.083	Major-Psychology	0.126 (0.332)	0.125	Language–Native Proficient	0.085 (0.279)	0.083
University–Southeast #2	0.085 (0.279)	0.083	Minor-Mathematics	0.252 (0.434)	0.250	Language–Nonnative Fluent	0.084 (0.277)	0.083
University–Midwest #1	0.083 (0.276)	0.083	Minor–History	0.245 (0.430)	0.250	Language–Nonnative Proficient	0.085 (0.279)	0.083
University–Midwest #2	0.083 (0.275)	0.083	GPA–3.8 and 4.0	0.250 (0.433)	0.250	Volunteer Work	0.250 (0.433)	0.250
University–Midwest #3	0.085 (0.278)	0.083	GPA-3.4 and 3.6	0.248 (0.432)	0.250	College Job–Sales	0.335 (0.472)	0.333
University – Northeast 1	0.084 (0.277)	0.083	GPA–3.0 and 3.2	0.250 (0.433)	0.250	College Job–Campus Employment	0.337 (0.473)	0.333
University–Northeast #2	0.085 (0.279)	0.083	Intern–Marketing Analyst	0.083 (0.276)	0.083	Study Abroad–Italy	0.035 (0.185)	0.031
University–Southwest #1	0.084 (0.278)	0.083	Intern–Financial Analyst	0.083 (0.277)	0.083	Study Abroad–Mexico	0.035 (0.184)	0.031
University–Southwest #2	0.080 (0.271)	0.083	Intern–Marketing Sales	0.083 (0.276)	0.083	Study Abroad–China	0.037 (0.188)	0.031
University–West #1	0.083 (0.276)	0.083	Intern–Financial Sales	0.082 (0.274)	0.083	Study Abroad–Dubai	0.035 (0.184)	0.031
University–West #2	0.084 (0.278)	0.083	Intern–General Research	0.083 (0.275)	0.083	Study Abroad–Argentina	0.036 (0.186)	0.031
Major–Finance	0.124 (0.330)	0.125	Intern–General Sales	0.082 (0.275)	0.083	Study Abroad–South Africa	0.036 (0.186)	0.031
Major–Marketing	0.126 (0.332)	0.125	Computer–Programming and Data Analysis	0.124 (0.330)	0.125	Study Abroad–Japan	0.036 (0.186)	0.031
Major–Anthropology	0.124 (0.329)	0.125	Computer–Programming	0.126 (0.331)	0.125	Cover Letter	0.250 (0.433)	0.250

Notes: Mean and standard deviations for each variable capturing the randomly assigned résumé credentials as well as the assigned probabilities. Each variable name includes a group identifier, such as ”Demographic”, ”University”, ”Major”, etc., followed by the name of the variable.

Table A2: Effects of Majors on Callback Rates (Without Controls)

	Baseline	By 2016/17–2019/20 Δ Occ. Wage		By Analytical Skills Intensity		By Interpersonal Skills Intensity	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Economics	1.70***	2.17***	1.28	0.24	2.88***	0.73	2.55***
	(0.60)‡ ‡ ‡	(0.76)‡ ‡ ‡	(0.91)	(0.91)	(0.79)‡ ‡ ‡	(0.92)	(0.78)‡ ‡ ‡
Finance	-0.10	0.61	-0.80	-1.72*	1.21	-1.56*	1.15
	(0.60)	(0.75)	(0.94)	(0.91)	(0.81)	(0.91)	(0.80)
Marketing	1.05*	1.59**	0.54	-0.48	2.29***	0.22	1.74**
	(0.60)	(0.79)	(0.90)	(0.87)	(0.82)‡ ‡ ‡	(0.89)	(0.81)
Psychology	0.58	0.29	0.83	-0.72	1.60**	-0.07	1.11
	(0.59)	(0.77)	(0.88)	(0.89)	(0.79)	(0.89)	(0.78)
Biology	1.97***	2.29***	1.65*	0.37	3.24***	0.81	2.95***
	(0.60)‡ ‡ ‡	(0.77)‡ ‡ ‡	(0.92)	(0.90)	(0.82)‡ ‡ ‡	(0.90)	(0.81)‡ ‡ ‡
Chemistry	1.45**	1.20	1.69*	1.10	1.69**	1.90**	1.02
	(0.60)‡‡	(0.76)	(0.92)	(0.88)	(0.82)	(0.91)	(0.80)
Anthropology	0.92	0.76	1.07	-0.38	1.95**	0.15	1.56*
	(0.60)	(0.75)	(0.92)	(0.89)	(0.80)‡‡	(0.89)	(0.80)
Heterogeneity split	-	Low	High	Low	High	Low	High
Controls	No	No	No	No	No	No	No
Job ad fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Callback mean	14.95	10.98	18.71	15.18	14.76	15.78	14.23
Callback mean, omitted category	13.56	10.05	16.92	15.04	12.39	15.09	12.28
Observations	36,880	17,912	18,968	16,748	20,132	17,260	19,620

Notes: Parameter estimates for callback returns to majors, estimated in equation (2). Callback dummy is multiplied by 100. Standard errors clustered at the job ad level in parentheses. The omitted category is a major in Philosophy.

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.
(based on p-values unadjusted for multiple-hypothesis testing).

‡ ‡ ‡ Significant at the 1 percent level.
‡‡ Significant at the 5 percent level.
‡ Significant at the 10 percent level.
(based on p-values adjusted for multiple-hypothesis testing).

Table A3: Effects of Minors on Callback Rates (Without Controls)

	Baseline	By 2016/17–2019/20 Δ Occ. Wage		By Analytical Skills Intensity		By Interpersonal Skills Intensity	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
History Minor	0.15	0.51	-0.19	-0.26	0.50	-0.02	0.31
	(0.36)	(0.45)	(0.57)	(0.54)	(0.49)	(0.56)	(0.48)
Math Minor	0.02	0.46	-0.39	0.15	-0.08	0.10	-0.04
	(0.36)	(0.48)	(0.54)	(0.55)	(0.49)	(0.54)	(0.50)
Heterogeneity split	-	Low	High	Low	High	Low	High
Controls	No	No	No	No	No	No	No
Job ad fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Callback mean	14.95	10.98	18.71	15.18	14.76	15.78	14.23
Callback mean, omitted category	14.81	10.85	18.57	15.18	14.50	15.61	14.11
Observations	36,880	17,912	18,968	16,748	20,132	17,260	19,620

Notes: Parameter estimates for callback returns to minors, estimated in equation (2). Callback dummy is multiplied by 100. Standard errors clustered at the job ad level in parentheses. The omitted category is no minor.

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.
(based on p-values unadjusted for multiple-hypothesis testing).

‡ ‡ ‡ Significant at the 1 percent level.
‡‡ Significant at the 5 percent level.
‡ Significant at the 10 percent level.
(based on p-values adjusted for multiple-hypothesis testing).

Table A4: Effects of Internships on Callback Rates (Without Controls)

	Baseline	By 2016/17–2019/20 Δ Occ. Wage		By Analytical Skills Intensity		By Interpersonal Skills Intensity	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Social Internship	1.17***	1.25***	1.10**	0.80	1.47***	0.86	1.44***
	(0.36)‡ ‡ ‡	(0.47)‡‡	(0.54)	(0.54)	(0.48)‡ ‡ ‡	(0.54)	(0.48)‡ ‡ ‡
Quantitative Internship	-0.02	-0.10	0.05	0.35	-0.32	0.30	-0.30
	(0.34)	(0.41)	(0.54)	(0.52)	(0.45)	(0.53)	(0.44)
Heterogeneity split	-	Low	High	Low	High	Low	High
Controls	No	No	No	No	No	No	No
Job ad fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Callback mean	14.95	10.98	18.71	15.18	14.76	15.78	14.23
Callback mean, omitted category	14.80	10.67	18.71	14.91	14.71	15.64	14.05
Observations	36,880	17,912	18,968	16,748	20,132	17,260	19,620

Notes: Parameter estimates for callback returns to internships, estimated in equation (2). Callback dummy is multiplied by 100. Standard errors clustered at the job ad level in parentheses. The omitted category is no internship.

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.
(based on p-values unadjusted for multiple-hypothesis testing).

‡ ‡ ‡ Significant at the 1 percent level.
‡‡ Significant at the 5 percent level.
‡ Significant at the 10 percent level.
(based on p-values adjusted for multiple-hypothesis testing).

Table A5: Effects of Study Abroad Experience on Callback Rates (Without Controls)

	Baseline	By 2016/17–2019/20 Δ Occ. Wage		By Analytical Skills Intensity		By Interpersonal Skills Intensity	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Study Abroad	0.78***	0.96**	0.62	0.55	0.98**	0.38	1.14***
	(0.30)‡‡	(0.37)‡‡	(0.46)	(0.45)	(0.40)‡‡	(0.45)	(0.40)‡ ‡ ‡
Heterogeneity split	-	Low	High	Low	High	Low	High
Controls	No	No	No	No	No	No	No
Job ad fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Callback mean	14.95	10.98	18.71	15.18	14.76	15.78	14.23
Callback mean, omitted category	14.76	10.74	18.55	15.05	14.52	15.68	13.94
Observations	36,880	17,912	18,968	16,748	20,132	17,260	19,620

Notes: Parameter estimates for callback returns to study abroad experience, estimated in equation (2). Callback dummy is multiplied by 100. Standard errors clustered at the job ad level in parentheses. The omitted category is no study abroad experience.

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.
(based on p-values unadjusted for multiple-hypothesis testing).

‡ ‡ ‡ Significant at the 1 percent level.
‡‡ Significant at the 5 percent level.
‡ Significant at the 10 percent level.
(based on p-values adjusted for multiple-hypothesis testing).

Table A6: Effects of Computer Skills on Callback Rates (Without Controls)

	Baseline	By 2016/17–2019/20 Δ Occ. Wage		By Analytical Skills Intensity		By Interpersonal Skills Intensity	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Basic Computer Skills	0.70*	0.27	1.12**	0.88	0.56	0.74	0.67
	(0.37)	(0.47)	(0.56)	(0.56)	(0.48)	(0.56)	(0.49)
Programming Skills	0.50	0.29	0.70	0.47	0.52	0.91	0.13
	(0.47)	(0.62)	(0.71)	(0.69)	(0.65)	(0.69)	(0.66)
Data Analysis Skills	0.38	-0.13	0.86	0.76	0.06	0.90	-0.08
	(0.37)	(0.47)	(0.57)	(0.55)	(0.50)	(0.56)	(0.49)
Programming and Data Analysis Skills	1.31***	1.00*	1.60**	1.54**	1.12*	1.13	1.46**
	(0.47)‡‡	(0.59)	(0.74)	(0.71)	(0.63)	(0.72)	(0.62)‡
Heterogeneity split	-	Low	High	Low	High	Low	High
Controls	No	No	No	No	No	No	No
Job ad fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Callback mean	14.95	10.98	18.71	15.18	14.76	15.78	14.23
Callback mean, omitted category	14.46	10.79	17.92	14.52	14.40	15.11	13.88
Observations	36,880	17,912	18,968	16,748	20,132	17,260	19,620

Notes: Parameter estimates for callback returns to computer skills, estimated in equation (2). Callback dummy is multiplied by 100. Standard errors clustered at the job ad level in parentheses. The omitted category is listing no computer skills.

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.
(based on *p*-values unadjusted for multiple-hypothesis testing).

‡ ‡ ‡ Significant at the 1 percent level.
‡‡ Significant at the 5 percent level.
‡ Significant at the 10 percent level.
(based on *p*-values adjusted for multiple-hypothesis testing).

B Classifying Job Ads and Incorporating External Data Sources (for online publication)

B.1 The O*NET-SOC Autocoder

The O*NET-SOC Autocoder is a proprietary machine learning algorithm (MLA) developed by the Department of Labor and improved by R.M. Wilson Consulting, Inc. The MLA uses as inputs the job title and job description to assign 8-digit O*NET-SOC codes. The initial sample size for the audit included 37,872 observations. However, 992 of these observations (i.e. 248 ads) were excluded from the data set due to the inability to link the ad to a O*NET-SOC code. We note that the main results (i.e. the effects of the résumé attributes on callback rates) are unaffected by the exclusion of these observations.

B.2 ACS and O*NET Data Integration for Heterogeneous Analysis

We classify occupations into low- and high-wage growth using ACS 2016-2020 employed workers, born between 1991 and 1996 (which mainly includes individuals who graduated in 2016 and 2017). We first calculated the average income by occupation for the years 2016 and 2017, using 5-digit SOC codes and labor-supply weights. These weights were obtained by multiplying the usual hours worked by the number of weeks worked. Following this, we calculated the three-year income growth for each year and then took the average. Lastly, we determined the median income growth across all the occupations in the audit sample, and divided the sample into two groups: those falling below the median income growth and those exceeding it.

For the division of our résumé sample based on task intensity, we follow the framework by Acemoglu and Autor (2011) that uses O*NET task measures. These are composite measures based on O*NET Work Activities Level scales. We focus on two of the five categories from Acemoglu and Autor (2011): non-routine cognitive analytical and non-routine cognitive interpersonal tasks. The analytical tasks include ”Analyzing Data/Information” (O*NET code 4.A.2.a.4), ”Thinking Creatively” (4.A.2.b.2), and ”Interpreting Information for Others” (4.A.4.a.1). The interpersonal tasks comprise ”Establishing and Maintaining Personal Relationships” (4.A.4.a.4), ”Guiding, Directing and Motivating Subordinates” (4.A.4.b.4), and ”Coaching/Developing Others” (4.A.4.b.5). To quantify these tasks, each activity is converted to a 0-10 scale and then averaged to form a composite score for each cognitive task category. These scores are aggregated at the occupation level using 6-digit SOC codes and labor-supply weights. The weights are computed from a sample of early-career, college-educated workers (ages 21-26) from the ACS data, by multiplying their usual hours worked by weeks worked. After obtaining these task intensity measures, we calculate the median intensity for both analytical and interpersonal skills across all the occupations in the audit sample, and subsequently divide the occupations into those falling above and below these medians. Because the ACS and O*NET data sets use different occupation codings, it is necessary to crosswalk between as well as within the two. The occupation code used in our analysis is based on the 2018 Standard Occupation Classification (SOC) system. Given that our calculations for the task intensity measures are based on pooled cross-sectional data from 2015-2018, we use the ACS crosswalks available from iPUMS to harmonize the occupation groupings. To merge the O*NET data to the ACS, we must also crosswalk the O*NET-SOC codes from 2010 to 2019 so that these data can be linked via the 2018 SOC codes. The last step is to link the ACS and O*NET data sets via the the 2019 O*NET-SOC to 2018 SOC crosswalk available from the O*NET website.