FOR ONLINE PUBLICATION ONLY

Online Appendix for *Incentivized Resume Rating: Eliciting Employer Preferences without Deception*

Judd B. Kessler, Corinne Low, Colin D. Sullivan

Appendices

We provide three appendices. In Appendix A, we describe the design of our experiment in detail, including recruitment materials (A.1), survey tool construction (A.2), and the candidate matching process (A.3). In Appendix B, we present additional analyses and results, including human capital results (B.1), regressions weighted by GPA (B.2), a discussion of preferences throughout the quality distribution (B.3), and a discussion of our discrimination results (B.4). In Appendix C, we discuss additional details related to replicating our experiment at Pitt.

A Experimental Design Appendix

A.1 Recruitment Materials

University of Pennsylvania Career Services sent recruitment materials to both recruiting firms and graduating seniors to participate in the study. All materials marketed the study as an additional tool to connect students with firms, rather than a replacement for any usual recruiting efforts. The recruitment email for employers, shown in Figure A.1, was sent to a list of contacts maintained by Career Services and promised to use a "newly developed machine-learning algorithm to identify candidates who would be a particularly good fit for your job based on your evaluations." In our replication at the University of Pittsburgh, a similar email was sent from the Pitt Office of Career Development and Placement Assistance. Penn Career Services recruited graduating seniors to participate as part of the candidate matching pool through their regular newsletter called the "Friday Flash." The relevant excerpt from this email newsletter is shown in Figure A.2.

We timed recruitment so that employers would receive their 10 resume matches around the time they were on campus in order to facilitate meeting the job seekers. In addition, we offered webinars for employers who were interested in learning about the survey screening experience before they participated. Employers could anonymously join a call where they viewed a slideshow about the survey software and could submit questions via chat box. Attendance at these webinars was low.

Figure A.1. : Employer Recruitment Email

From: upenn@csm.symplicity.com [mailto:upenn@csm.symplicity.com]
Sent: Tuesday, July 26, 2016 1:34 PM
To: [redacted]
Subject: Identify Top Penn Students for your Firm

Dear [redacted]

This year, Penn Career Services is participating in a pilot with two Wharton professors who are developing a new tool that can help you to identify potential job candidates from the University of Pennsylvania for post-graduate positions.

The tool is designed to identify top candidates for your open positions and provides you with those candidates' contact information and resumes so you can invite them to coffee chats, to info sessions, and to apply for a job at your organization. Since the tool uses data-driven methods to identify candidates, we see this as a useful complement to firms' existing methods for identifying promising candidates.

Completing the tool takes about 30 minutes and involves evaluating 40 hypothetical resumes. After evaluating these resumes, the tool uses a newly developed machine-learning algorithm to identify candidates who would be a particularly good fit for your job based on your evaluations. The Wharton professors will also use a completely anonymized version of your data to perform research on broader trends in what firms value in hiring, and they will be glad to share these insights with your company once the research is complete. To be provided with potential candidates for a position, at least one person from your firm must complete the tool. If possible, having multiple individuals participate will help increase the accuracy of the algorithm's recommendations. Additionally, if you are hiring for different positions within your organization, we recommend at least one person from your organization take the tool for each open position so you get a list of candidates tailored for each job opening. Rising Penn seniors will be invited to participate in the trial by submitting their resumes beginning on August 22nd, and we plan to have candidate recommendations to you by early September.

To take the tool, please click the link here:

https://wharton.qualtrics.com/SE/?SID=SV_3l3ohtNPn2R8c97

If you you would like to discuss more about how the tool could be useful for your firm, or have any questions, please contact the Wharton researchers: Judd B. Kessler (judd.kessler@wharton.upenn.edu) and Corinne Low (corlow@wharton.upenn.edu).

Sincerely,

Barbara Hewitt, Senior Associate Director, Career Services

Email sent to firms recruiting at Penn originating from the Senior Associate Director of Career Services at the University of Pennsylvania. Subjects who followed the link in the email were taken to the instructions (Figure A.3).

Figure A.2. : Email Announcement to Graduating Seniors

From: Career Services - Wharton Class of 2017 <CAREERSERVICES2017@LISTS.UPENN.EDU> On Behalf Of Ross, S. David
Sent: Friday, August 26, 2016 5:20 PM
To: CAREERSERVICES2017@LISTS.UPENN.EDU
Subject: Wharton Seniors: Penn Career Services Senior Friday Flash, August 26, 2016

Welcome back! I hope you had a wonderful and productive summer. This is the first issue of the senior Career Services Friday Flash for the year. Barbara Hewitt is the Senior Associate Director in the Career Services office working with Wharton undergraduate students and alumni - she will manage the Career Services listserv for Wharton seniors and will be sending you weekly Friday Flash e-mails to keep you updated on workshops, job postings, employer presentations, career resources and more. Barbara and I look forward to working with you this year as you begin (or continue!) to think about life after Penn. Please do come in to speak with either of us about your plans. Also, please note that On Campus Recruiting activities have started, so don't delay if you would like to participate!

[OTHER TEXT APPEARED HERE]

Announcements

An Opportunity To Reach More Employers

This year, Penn Career Services is working with two Wharton professors on a pilot that can help you get noticed by top employers in all fields. Wharton professors Judd B. Kessler and Corinne Low have developed a tool that analyzes employer preferences for job candidates and then uses machine learning to identify Penn seniors who may be a good fit for the employer's positions. Employers across a variety of industries (e.g. consulting, finance, technology, etc.) have already participated in the pilot by providing preferences for job candidates. Upload your resume now to be eligible to participate! Only candidates who upload their resume through this link can participate in the pilot. To upload your resume, click here: https://wharton.qualtrics.com/SE/?SID=SV_bryPbgBn4rEXD0h. If you have any questions about the pilot, please contact the Wharton professors running it: Judd B. Kessler (judd.kessler@wharton.upenn.edu) and Corinne Low (corlow@wharton.upenn.edu). (Note: this pilot will be run in parallel to all existing recruiting activities.)

Excerpt from email newsletter sent to the Career Services office mailing list. The email originated from the staff members at Penn Career Services. Students following the link were taken to a survey page where they were asked to upload their resumes and to answer a brief questionnaire about their job search (page not shown).

A.2 Survey Tool Design

In this section, we describe the process of generating hypothetical resumes. This appendix should serve to provide additional details about the selection and randomization of resume components, and as a guide to researchers wishing to implement our methodology. In Section A.2.1, we describe the structure of the IRR survey tool and participant experience. In Section A.2.2, we describe the structure of our hypothetical resumes. In Section A.2.3, we detail the randomization of candidate gender and race through names. Section A.2.4 details the randomization of educational background. Section A.2.5 describes the process we used to collect and scrape real resume components to randomize work experience, leadership experience, and skills.

A.2.1 Survey Tool Structure

We constructed the survey tool using Qualtrics software for respondents to access from a web browser. Upon opening the survey link, respondents must enter an email address on the instructions page (see Figure A.3) to continue. Respondents then select the major type of candidates they will evaluate for their open position, either "Business (Wharton), Social Sciences, and Humanities" or "Science, Engineering, Computer Science, and Math" (see Figure A.4). In addition, they may enter the position title they are looking to fill. The position title is not used in determining the content of the hypothetical candidate resumes. After this selection, the randomization software populates 40 resumes for the respondent to evaluate, drawing on different content by major type. The subject then evaluates 40 hypothetical resumes. After every 10 resumes, a break page appears and encourages subjects to continue.

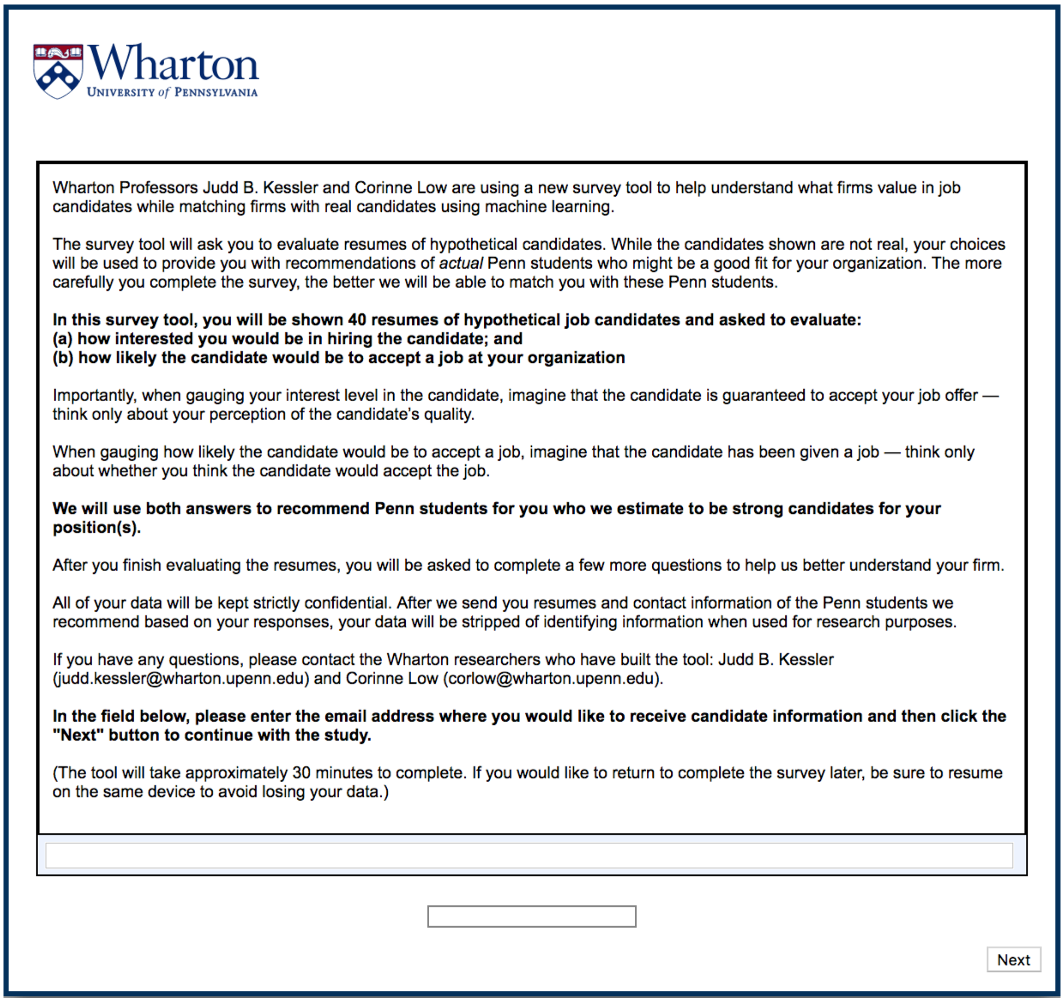
A.2.2 Resume Structure

We designed our resumes to combine realism with the requirements of experimental identification. We designed 10 resume templates to use as the basis for the 40 resumes in the tool. Each template presented the same information, in the same order, but with variations in page layout and font. Figures A.5 and A.6 show sample resume templates. All resumes contained five sections, in the following order: Personal Information (including name and blurred contact information); Education (GPA, major, school within university); Work Experience; Leadership Experience; and Skills.[36] While the real student resumes we encountered varied in content, most contained some subset of these sections. Since our main objective with resume variation was to improve realism for each subject rather than to test the effectiveness of different resume formats, we did not vary the order of the resume formats across subjects. In other words, the first resume always had the same font and

[36]These sections were not always labelled as such on candidate resumes. Personal Information was generally not identified, though each resume contained a name and blurred text in place of contact information. Skills were also marked as "Skills & Interests" and "Skill Summary".

page layout for each subject, although the content of the resume differed each time. Given that formats are in a fixed order in the 40 hypothetical resumes, the order fixed effects included in most specifications control for any effect of resume format. Resumes templates were built in HTML/CSS for display in a web browser, and populated dynamically in Qualtrics using JavaScript. Randomization occurred for all 40 resumes simultaneously, without replacement, each time a subject completed the instructions and selected their major category of interest. Each resume layout was flexible enough to accommodate different numbers of bullet points for each experience, and different numbers of work experiences. For example, if only one job was listed on the resume, the work experience section of the resume appeared shorter rather than introducing empty space.

Figure A.3. : Survey Tool Instructions & Contact Information



Wharton
UNIVERSITY of PENNSYLVANIA

Wharton Professors Judd B. Kessler and Corinne Low are using a new survey tool to help understand what firms value in job candidates while matching firms with real candidates using machine learning.

The survey tool will ask you to evaluate resumes of hypothetical candidates. While the candidates shown are not real, your choices will be used to provide you with recommendations of *actual* Penn students who might be a good fit for your organization. The more carefully you complete the survey, the better we will be able to match you with these Penn students.

In this survey tool, you will be shown 40 resumes of hypothetical job candidates and asked to evaluate:
(a) how interested you would be in hiring the candidate; and
(b) how likely the candidate would be to accept a job at your organization

Importantly, when gauging your interest level in the candidate, imagine that the candidate is guaranteed to accept your job offer — think only about your perception of the candidate's quality.

When gauging how likely the candidate would be to accept a job, imagine that the candidate has been given a job — think only about whether you think the candidate would accept the job.

We will use both answers to recommend Penn students for you who we estimate to be strong candidates for your position(s).

After you finish evaluating the resumes, you will be asked to complete a few more questions to help us better understand your firm.

All of your data will be kept strictly confidential. After we send you resumes and contact information of the Penn students we recommend based on your responses, your data will be stripped of identifying information when used for research purposes.

If you have any questions, please contact the Wharton researchers who have built the tool: Judd B. Kessler (judd.kessler@wharton.upenn.edu) and Corinne Low (corlow@wharton.upenn.edu).

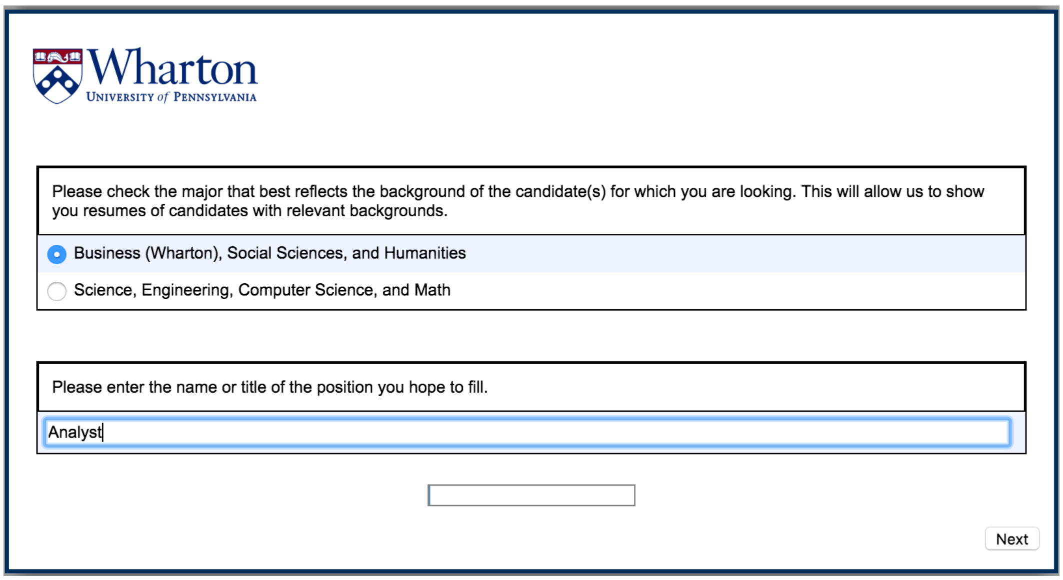
In the field below, please enter the email address where you would like to receive candidate information and then click the "Next" button to continue with the study.

(The tool will take approximately 30 minutes to complete. If you would like to return to complete the survey later, be sure to resume on the same device to avoid losing your data.)

Next

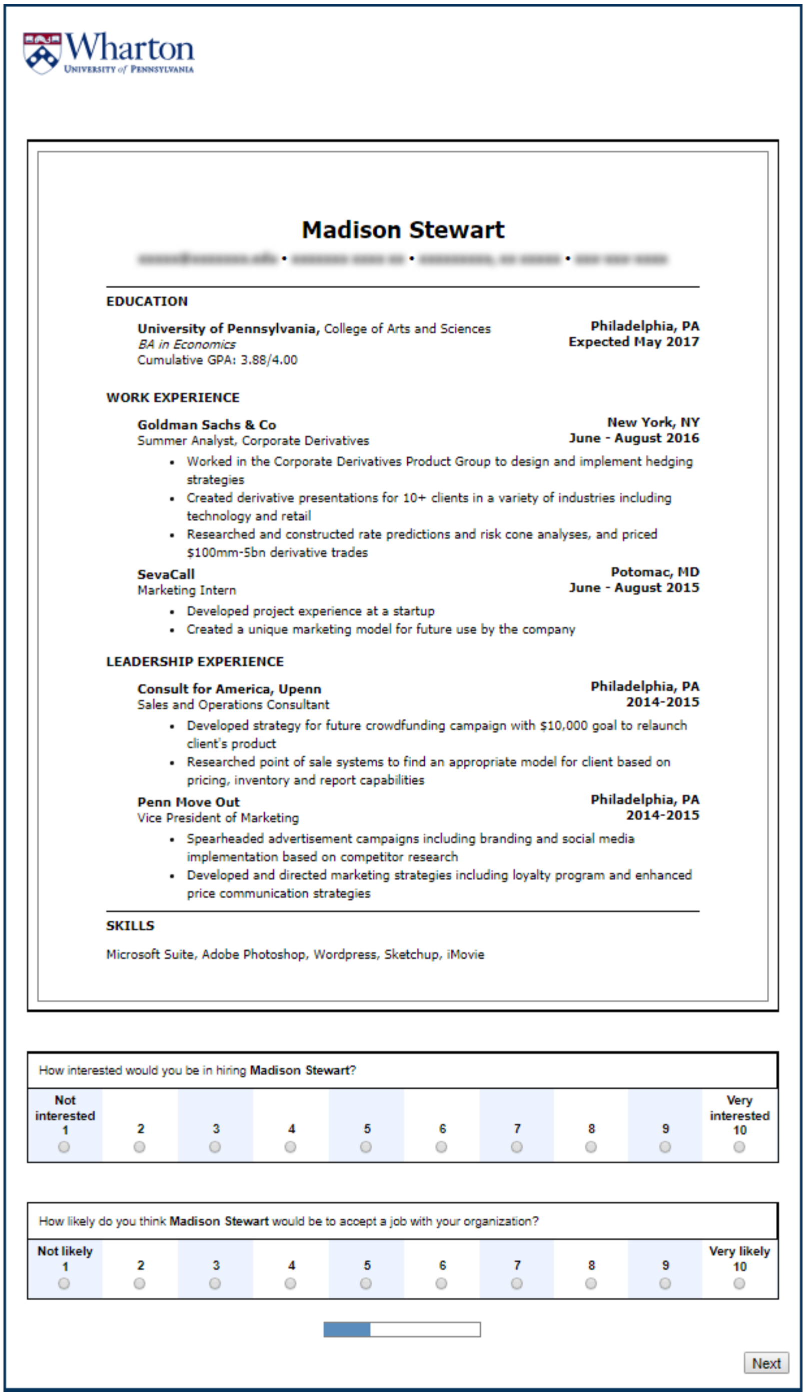
Screenshot of the instructions at the start of the survey tool. Subjects entered an email address at the bottom of the screen to proceed with the study; the resumes of the 10 real job seekers used as an incentive to participate were sent to this email address.

Figure A.4. : Major Type Selection



Screenshot of major selection page, as shown to subjects recruiting at the University of Pennsylvania. Subjects must select either "Business (Wharton), Social Sciences, and Humanities" or "Science, Engineering, Computer Science, and Math." Subjects may also enter the name of the position they wish to fill in the free text box; the information in this box was not used for analysis. Here, we have selected "Business (Wharton), Social Sciences, and Humanities" and entered "Analyst" as a demonstration only—by default all radio boxes and text boxes were empty for all subjects.

Figure A.5. : Sample Resume



Wharton
UNIVERSITY of PENNSYLVANIA

Madison Stewart

EDUCATION

University of Pennsylvania, College of Arts and Sciences — **Philadelphia, PA**
BA in Economics — **Expected May 2017**
Cumulative GPA: 3.88/4.00

WORK EXPERIENCE

Goldman Sachs & Co — **New York, NY**
Summer Analyst, Corporate Derivatives — **June - August 2016**
- Worked in the Corporate Derivatives Product Group to design and implement hedging strategies
- Created derivative presentations for 10+ clients in a variety of industries including technology and retail
- Researched and constructed rate predictions and risk cone analyses, and priced $100mm-5bn derivative trades

SevaCall — **Potomac, MD**
Marketing Intern — **June - August 2015**
- Developed project experience at a startup
- Created a unique marketing model for future use by the company

LEADERSHIP EXPERIENCE

Consult for America, Upenn — **Philadelphia, PA**
Sales and Operations Consultant — **2014-2015**
- Developed strategy for future crowdfunding campaign with $10,000 goal to relaunch client's product
- Researched point of sale systems to find an appropriate model for client based on pricing, inventory and report capabilities

Penn Move Out — **Philadelphia, PA**
Vice President of Marketing — **2014-2015**
- Spearheaded advertisement campaigns including branding and social media implementation based on competitor research
- Developed and directed marketing strategies including loyalty program and enhanced price communication strategies

SKILLS

Microsoft Suite, Adobe Photoshop, Wordpress, Sketchup, iMovie

How interested would you be in hiring **Madison Stewart**?

Not interested 1	2	3	4	5	6	7	8	9	Very interested 10

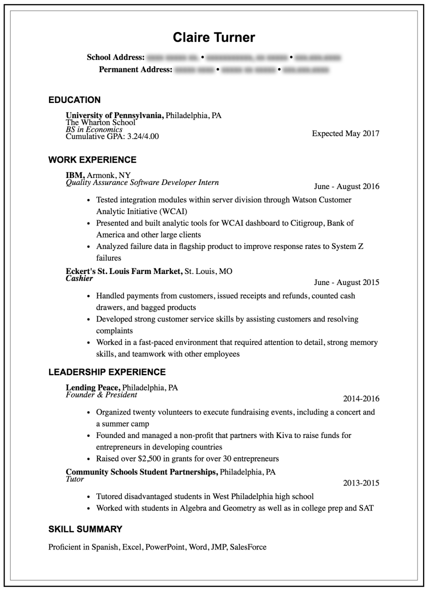
How likely do you think **Madison Stewart** would be to accept a job with your organization?

Not likely 1	2	3	4	5	6	7	8	9	Very likely 10

Next

A sample resume rating page from the Incentivized Resume Rating tool. Each resume is dynamically generated when the subject begins the study. Each resume has five sections: Personal Information (including first and last name, and blurred text to represent contact information); Education Information (university, school within university, degree, major, GPA, and expected graduation date); Work Experience (one or two experiences with employer name, location, job title, date, and descriptive bullet points); Leadership Experience (two experiences with organization, location, position title, date, and descriptive bullet points); and Skills. Resume randomization described in detail in Section I and Appendix A.2. At the bottom of each resume, subjects must respond to two questions before proceeding: "How interested would you be in hiring **[Name]**?" and "How likely do you think **[Name]** would be to accept a job with your organization?"

Figure A.6. : Four Sample Resumes



Claire Turner

School Address: [redacted]

Permanent Address: [redacted]

EDUCATION

University of Pennsylvania, Philadelphia, PA
The Wharton School
BS in Economics
Cumulative GPA: 3.24/4.00 Expected May 2017

WORK EXPERIENCE

IBM, Armonk, NY
Quality Assurance Software Developer Intern June - August 2016

- Tested integration modules within server division through Watson Customer Analytic Initiative (WCAI)
- Presented and built analytic tools for WCAI dashboard to Citigroup, Bank of America and other large clients
- Analyzed failure data in flagship product to improve response rates to System Z failures

Eckert's St. Louis Farm Market, St. Louis, MO
Cashier June - August 2015

- Handled payments from customers, issued receipts and refunds, counted cash drawers, and bagged products
- Developed strong customer service skills by assisting customers and resolving complaints
- Worked in a fast-paced environment that required attention to detail, strong memory skills, and teamwork with other employees

LEADERSHIP EXPERIENCE

Lending Peace, Philadelphia, PA
Founder & President 2014-2016

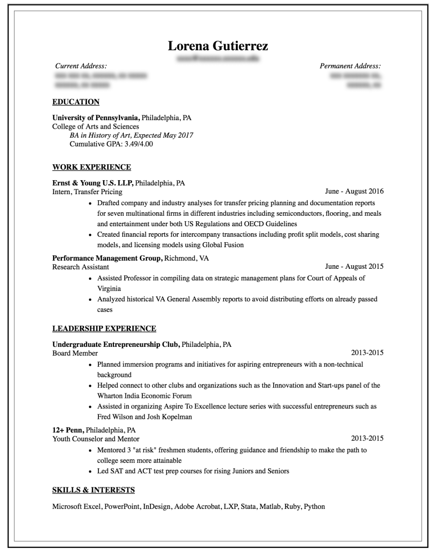
- Organized twenty volunteers to execute fundraising events, including a concert and a summer camp
- Founded and managed a non-profit that partners with Kiva to raise funds for entrepreneurs in developing countries
- Raised over $2,500 in grants for over 30 entrepreneurs

Community Schools Student Partnerships, Philadelphia, PA
Tutor 2013-2015

- Tutored disadvantaged students in West Philadelphia high school
- Worked with students in Algebra and Geometry as well as in college prep and SAT

SKILL SUMMARY

Proficient in Spanish, Excel, PowerPoint, Word, JMP, SalesForce



Lorena Gutierrez

[redacted]

Current Address: [redacted] *Permanent Address:* [redacted]

EDUCATION

University of Pennsylvania, Philadelphia, PA
College of Arts and Sciences
BA in History of Art, Expected May 2017
Cumulative GPA: 3.49/4.00

WORK EXPERIENCE

Ernst & Young U.S. LLP, Philadelphia, PA
Intern, Transfer Pricing June - August 2016

- Drafted company and industry analyses for transfer pricing planning and documentation reports for seven multinational firms in different industries including semiconductors, flooring, and meals and entertainment under both US Regulations and OECD Guidelines
- Created financial reports for intercompany transactions including profit split models, cost sharing models, and licensing models using Global Fusion

Performance Management Group, Richmond, VA
Research Assistant June - August 2015

- Assisted Professor in compiling data on strategic management plans for Court of Appeals of Virginia
- Analyzed historical VA General Assembly reports to avoid distributing efforts on already passed cases

LEADERSHIP EXPERIENCE

Undergraduate Entrepreneurship Club, Philadelphia, PA
Board Member 2013-2015

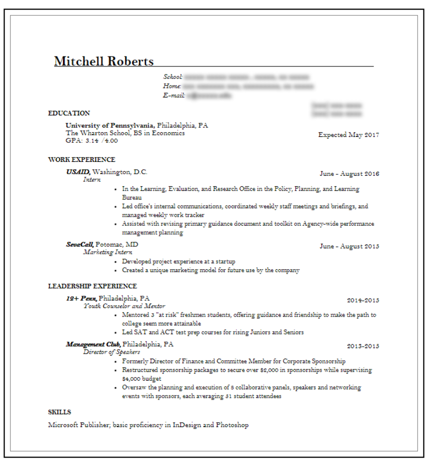
- Planned immersion programs and initiatives for aspiring entrepreneurs with a non-technical background
- Helped connect to other clubs and organizations such as the Innovation and Start-ups panel of the Wharton India Economic Forum
- Assisted in organizing Aspire To Excellence lecture series with successful entrepreneurs such as Fred Wilson and Josh Kopelman

12+ Penn, Philadelphia, PA
Youth Counselor and Mentor 2013-2015

- Mentored 3 "at risk" freshmen students, offering guidance and friendship to make the path to college seem more attainable
- Led SAT and ACT test prep courses for rising Juniors and Seniors

SKILLS & INTERESTS

Microsoft Excel, PowerPoint, InDesign, Adobe Acrobat, LXP, Stata, Matlab, Ruby, Python



Mitchell Roberts

School: [redacted]
Home: [redacted]
E-mail: [redacted]

EDUCATION

University of Pennsylvania, Philadelphia, PA
The Wharton School, BS in Economics Expected May 2017
GPA: 3.14 /4.00

WORK EXPERIENCE

USAID, Washington, D.C. June - August 2016
Intern

- In the Learning, Evaluation, and Research Office in the Policy, Planning, and Learning Bureau
- Led office's internal communications, coordinated weekly staff meetings and briefings, and managed weekly work tracker
- Assisted with revising primary guidance document and toolkit on Agency-wide performance management planning

SevaCall, Potomac, MD June - August 2015
Marketing Intern

- Developed project experience at a startup
- Created a unique marketing model for future use by the company

LEADERSHIP EXPERIENCE

12+ Penn, Philadelphia, PA 2014-2015
Youth Counselor and Mentor

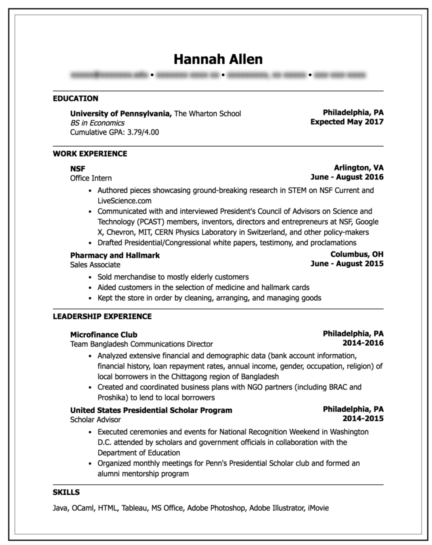
- Mentored 3 "at risk" freshmen students, offering guidance and friendship to make the path to college seem more attainable
- Led SAT and ACT test prep courses for rising Juniors and Seniors

Management Club, Philadelphia, PA 2013-2015
Director of Speakers

- Formerly Director of Finance and Committee Member for Corporate Sponsorship
- Restructured sponsorship packages to secure over $2,000 in sponsorships while supervising $4,000 budget
- Oversaw the planning and execution of 8 collaborative panels, speakers and networking events with sponsors, each averaging 31 student attendees

SKILLS

Microsoft Publisher; basic proficiency in InDesign and Photoshop



Hannah Allen

[redacted]

EDUCATION

University of Pennsylvania, The Wharton School **Philadelphia, PA**
BS in Economics **Expected May 2017**
Cumulative GPA: 3.79/4.00

WORK EXPERIENCE

NSF **Arlington, VA**
Office Intern **June - August 2016**

- Authored pieces showcasing ground-breaking research in STEM on NSF Current and LiveScience.com
- Communicated with and interviewed President's Council of Advisors on Science and Technology (PCAST) members, inventors, directors and entrepreneurs at NSF, Google X, Chevron, MIT, CERN Physics Laboratory in Switzerland, and other policy-makers
- Drafted Presidential/Congressional white papers, testimony, and proclamations

Pharmacy and Hallmark **Columbus, OH**
Sales Associate **June - August 2015**

- Sold merchandise to mostly elderly customers
- Aided customers in the selection of medicine and hallmark cards
- Kept the store in order by cleaning, arranging, and managing goods

LEADERSHIP EXPERIENCE

Microfinance Club **Philadelphia, PA**
Team Bangladesh Communications Director **2014-2016**

- Analyzed extensive financial and demographic data (bank account information, financial history, loan repayment rates, annual income, gender, occupation, religion) of local borrowers in the Chittagong region of Bangladesh
- Created and coordinated business plans with NGO partners (including BRAC and Proshika) to lend to local borrowers

United States Presidential Scholar Program **Philadelphia, PA**
Scholar Advisor **2014-2015**

- Executed ceremonies and events for National Recognition Weekend in Washington D.C. attended by scholars and government officials in collaboration with the Department of Education
- Organized monthly meetings for Penn's Presidential Scholar club and formed an alumni mentorship program

SKILLS

Java, OCaml, HTML, Tableau, MS Office, Adobe Photoshop, Adobe Illustrator, iMovie

Four sample resumes generated by the survey tool. Note that the resumes each have a different format, differentiated by elements such as font, boldface type, horizontal rules, location of information, and spacing. All resumes have the same five sections: Personal Information, Education, Work Experience, Leadership Experience, and Skills. Resumes differ in length based on the dynamically selected content, such as the randomized number of work experiences and the (non-randomized) number of description bullet points associated with an experience.

A.2.3 Names

A hypothetical candidate name appears as the first element on each resume. Names were generated to be highly indicative of race and gender, following the approach of Fryer and Levitt (2004). As described in Section C, first names were selected from a dataset of all births in the state of Massachusetts between 1989-1996 and in New York City between 1990-1996. These years reflect the approximate birth years of the job seekers in our study. We identified 100 first names with the most indicative race and gender for each of the following race-gender combinations: Asian Female, Asian Male, Black Female, Black Male, Hispanic Female, Hispanic Male, White Female, and White Male. We then eliminated names that were gender-ambiguous in the broad sample even if they might be unambiguous within an ethnic group. We also eliminated names strongly indicative of religion. We followed a similar process for last names, using name and ethnicity data from the 2000 Census. Finally, we paired first and last names together by race and selected 50 names for each race-gender combination for randomization. Names of hypothetical female candidates are shown in Table A.1; names of hypothetical male candidates are shown in Table A.2.

At the point of randomization, names were drawn without replacement according to a distribution of race and gender intended to reflect the US population (50% female, 50% male; 65.7% White, 16.8% Hispanic, 12.6% Black, 4.9% Asian). Gender and race were randomized independently. In other words, we selected either Table A.1 or Table A.2 with equal probability, then selected a column to draw from according to the race probabilities. Finally, names were selected uniformly and without replacement from the appropriate column of the table. We use the variation induced by these names for the analysis variables *Female, White*; *Male, Non-White*; *Female, Non-White*; and *Not a White Male*.

A.2.4 Education

We randomized two components in the Education section of each resume: grade point average (GPA) and major. The degree (BA or BS) and the name of the degree-granting school within Penn was linked to the randomly selected major. We also provided an expected graduation date (fixed to May 2017 for all students) and the name of the university (University of Pennsylvania).

GPA — We selected GPA from a $Unif[2.90, 4.00]$ distribution, rounding to the nearest hundredth. We chose to include GPA on all resumes, although some students omit GPA on real resumes. We decided to avoid the complexity of forcing subjects to make inferences about missing GPAs. The range was selected to approximate the range of GPAs observed on real resumes. We chose a uniform distribution (rather than, say, a Gaussian) to increase our power to identify preferences throughout the distribution. We did not specify GPA within major on any resumes. We use this variation to define the variable *GPA*.

Table A.1—Female Names Populating Resume Tool

Asian Female	Black Female	Hispanic Female	White Female
Tina Zheng	Jamila Washington	Ivette Barajas	Allyson Wood
Annie Xiong	Asia Jefferson	Nathalie Orozco	Rachael Sullivan
Julie Xu	Essence Banks	Mayra Zavala	Katharine Myers
Michelle Zhao	Monique Jackson	Luisa Velazquez	Colleen Peterson
Linda Zhang	Tianna Joseph	Jessenia Meza	Meghan Miller
Anita Zhu	Janay Mack	Darlene Juarez	Meaghan Murphy
Alice Jiang	Nia Williams	Thalia Ibarra	Lindsey Fisher
Esther Zhou	Latoya Robinson	Perla Cervantes	Paige Cox
Winnie Thao	Jalisa Coleman	Lissette Huerta	Katelyn Cook
Susan Huang	Imani Harris	Daisy Espinoza	Jillian Long
Sharon Yang	Malika Sims	Cristal Vazquez	Molly Baker
Gloria Hwang	Keisha James	Paola Cisneros	Heather Nelson
Diane Ngo	Shanell Thomas	Leticia Gonzalez	Alison Hughes
Carmen Huynh	Janae Dixon	Jesenia Hernandez	Bridget Kelly
Angela Truong	Latisha Daniels	Alejandra Contreras	Hayley Russell
Janet Kwon	Zakiya Franklin	Iliana Ramirez	Carly Roberts
Janice Luong	Kiana Jones	Julissa Esparza	Bethany Phillips
Irene Cheung	Ayana Grant	Giselle Alvarado	Kerry Bennett
Amy Choi	Ayanna Holmes	Gloria Macias	Kara Morgan
Shirley Yu	Shaquana Frazier	Selena Zuniga	Kaitlyn Ward
Kristine Nguyen	Shaniqua Green	Maribel Ayala	Audrey Rogers
Cindy Wu	Tamika Jenkins	Liliana Mejia	Jacquelyn Martin
Joyce Vu	Akilah Fields	Arlene Rojas	Marissa Anderson
Vivian Hsu	Shantel Simmons	Cristina Ochoa	Haley Clark
Jane Liang	Shanique Carter	Yaritza Carillo	Lindsay Campbell
Maggie Tsai	Tiara Woods	Guadalupe Rios	Cara Adams
Diana Pham	Tierra Bryant	Angie Jimenez	Jenna Morris
Wendy Li	Raven Brown	Esmeralda Maldonado	Caitlin Price
Sally Hoang	Octavia Byrd	Marisol Cardenas	Kathryn Hall
Kathy Duong	Tyra Walker	Denisse Chavez	Emma Bailey
Lily Vang	Diamond Lewis	Gabriela Mendez	Erin Collins
Helen Trinh	Nyasia Johnson	Jeanette Rosales	Marisa Reed
Sandy Oh	Aliyah Douglas	Rosa Castaneda	Madeleine Smith
Christine Tran	Aaliyah Alexander	Beatriz Rodriguez	Mackenzie King
Judy Luu	Princess Henderson	Yessenia Acevedo	Sophie Thompson
Grace Cho	Shanae Richardson	Carolina Guzman	Madison Stewart
Nancy Liu	Kenya Brooks	Carmen Aguilar	Margaret Parker
Lisa Cheng	Charisma Scott	Yesenia Vasquez	Kristin Gray
Connie Yi	Shante Hunter	Ana Munoz	Michaela Evans
Tiffany Phan	Jada Hawkins	Xiomara Ortiz	Jaclyn Cooper
Karen Lu	Shanice Reid	Lizbeth Rivas	Hannah Allen
Tracy Chen	Chanelle Sanders	Genesis Sosa	Zoe Wilson
Betty Dinh	Shanequa Bell	Stephany Salinas	Caitlyn Young
Anna Hu	Shaniece Mitchell	Lorena Gutierrez	Charlotte Moore
Elaine Le	Ebony Ford	Emely Sandoval	Kaitlin Wright
Sophia Ly	Tanisha Watkins	Iris Villarreal	Holly White
Jenny Vo	Shanelle Butler	Maritza Garza	Kate Taylor
Monica Lin	Precious Davis	Marilyn Arroyo	Krista Hill
Joanne Yoon	Asha Willis	Lourdes Soto	Meredith Howard
Priya Patel	Ashanti Edwards	Gladys Herrera	Claire Turner

Names of hypothetical female candidates. 50 names were selected to be highly indicative of each combination of race and gender. A name drawn from these lists was displayed at the top of each hypothetical resume, and in the questions used to evaluate the resumes. First and last names were linked every time they appeared. For details on the construction and randomization of names, see Section C and Appendix A.2.3.

Table A.2—Male Names Populating Resume Tool

Asian Male	**Black Male**	**Hispanic Male**	**White Male**
Richard Thao	Rashawn Washington	Andres Barajas	Kyle Wood
Samuel Truong	Devonte Jefferson	Julio Orozco	Derek Sullivan
Daniel Cheung	Marquis Banks	Marcos Zavala	Connor Myers
Alan Tsai	Tyree Jackson	Mike Velazquez	Douglas Peterson
Paul Li	Lamont Joseph	Jose Meza	Spencer Miller
Steven Zhang	Jaleel Mack	Alfredo Juarez	Jackson Murphy
Matthew Zheng	Javon Williams	Fernando Ibarra	Bradley Fisher
Alex Vu	Darryl Robinson	Gustavo Cervantes	Drew Cox
Joshua Vo	Kareem Coleman	Adonis Huerta	Lucas Cook
Brandon Lu	Kwame Harris	Juan Espinoza	Evan Long
Henry Dinh	Deshawn Sims	Jorge Vazquez	Adam Baker
Philip Hsu	Terrell James	Abel Cisneros	Harrison Nelson
Eric Liang	Akeem Thomas	Cesar Gonzalez	Brendan Hughes
David Yoon	Daquan Dixon	Alberto Hernandez	Cody Kelly
Jonathan Yu	Tarik Daniels	Elvin Contreras	Zachary Russell
Andrew Trinh	Jaquan Franklin	Ruben Ramirez	Mitchell Roberts
Stephen Yi	Tyrell Jones	Reynaldo Esparza	Tyler Phillips
Ryan Nguyen	Isiah Grant	Wilfredo Alvarado	Matthew Bennett
Aaron Jiang	Omari Holmes	Francisco Macias	Thomas Morgan
Kenneth Zhao	Rashad Frazier	Emilio Zuniga	Sean Ward
Johnny Hwang	Jermaine Green	Javier Ayala	Nicholas Rogers
Tony Choi	Donte Jenkins	Guillermo Mejia	Brett Martin
Benjamin Luong	Donnell Fields	Elvis Rojas	Cory Anderson
Raymond Tran	Davon Simmons	Miguel Ochoa	Colin Clark
Michael Duong	Darnell Carter	Sergio Carillo	Jack Campbell
Andy Hoang	Hakeem Woods	Alejandro Rios	Ross Adams
Alexander Pham	Sheldon Bryant	Ernesto Jimenez	Liam Morris
Robert Yang	Antoine Brown	Oscar Maldonado	Max Price
Danny Xu	Marquise Byrd	Felix Cardenas	Ethan Hall
Anthony Huynh	Tyrone Walker	Manuel Chavez	Eli Bailey
Jason Liu	Dashawn Lewis	Orlando Mendez	Patrick Collins
John Chen	Shamel Johnson	Luis Rosales	Luke Reed
Brian Vang	Reginald Douglas	Eduardo Castaneda	Alec Smith
Joseph Zhou	Shaquille Alexander	Carlos Rodriguez	Seth King
James Cho	Jamel Henderson	Cristian Acevedo	Austin Thompson
Nicholas Lin	Akil Richardson	Pedro Guzman	Nathan Stewart
Jeffrey Huang	Tyquan Brooks	Freddy Aguilar	Jacob Parker
Christopher Wu	Jamal Scott	Esteban Vasquez	Craig Gray
Timothy Ly	Jabari Hunter	Leonardo Munoz	Garrett Evans
William Oh	Tyshawn Hawkins	Arturo Ortiz	Ian Cooper
Patrick Ngo	Demetrius Reid	Jesus Rivas	Benjamin Allen
Thomas Cheng	Denzel Sanders	Ramon Sosa	Conor Wilson
Vincent Le	Tyreek Bell	Enrique Salinas	Jared Young
Kevin Hu	Darius Mitchell	Hector Gutierrez	Theodore Moore
Jimmy Xiong	Prince Ford	Armando Sandoval	Shane Wright
Justin Zhu	Lamar Watkins	Roberto Villarreal	Scott White
Calvin Luu	Raheem Butler	Edgar Garza	Noah Taylor
Edward Kwon	Jamar Davis	Pablo Arroyo	Ryan Hill
Peter Phan	Tariq Willis	Raul Soto	Jake Howard
Victor Patel	Shaquan Edwards	Diego Herrera	Maxwell Turner

Names of hypothetical male candidates. 50 names were selected to be highly indicative of each combination of race and gender. A name drawn from these lists was displayed at the top of each hypothetical resume, and in the questions used to evaluate the resumes. First and last names were linked every time they appeared. For details on the construction and randomization of names, see Section C and Appendix A.2.3.

Major — Majors for the hypothetical resumes were selected with replacement according to a predefined probability distribution intended to balance the realism of the rating experience and our ability to detect and control for the effect of majors. Table A.3 shows each major along with its school affiliation and classification as "Business (Wharton), Social Sciences, and Humanities" (i.e., "Humanities & Social Sciences") or "Science, Engineering, Computer Science, and Math" (i.e., STEM), as well as the probability assigned to each. We use this variation as the variable *Major* and control for it with fixed effects in most regressions.

Table A.3—Majors in Generated Penn Resumes

Type	**School**	**Major**	**Probability**
Humanities & Social Sciences	The Wharton School	BS in Economics	0.4
	College of Arts and Sciences	BA in Economics	0.2
		BA in Political Science	0.075
		BA in Psychology	0.075
		BA in Communication	0.05
		BA in English	0.05
		BA in History	0.05
		BA in History of Art	0.025
		BA in Philosophy	0.025
		BA in International Relations	0.025
		BA in Sociology	0.025
STEM	School of Engineering and Applied Science	BS in Computer Engineering	0.15
		BS in Biomedical Science	0.075
		BS in Mechanical Engineering and Applied Mechanics	0.075
		BS in Bioengineering	0.05
		BS in Chemical and Biomolecular Engineering	0.05
		BS in Cognitive Science	0.05
		BS in Computational Biology	0.05
		BS in Computer Science	0.05
		BS in Electrical Engineering	0.05
		BS in Materials Science and Engineering	0.05
		BS in Networked and Social Systems Engineering	0.025
		BS in Systems Science and Engineering	0.025
	College of Arts and Sciences	BA in Biochemistry	0.05
		BA in Biology	0.05
		BA in Chemistry	0.05
		BA in Cognitive Science	0.05
		BA in Mathematics	0.05
		BA in Physics	0.05

Majors, degrees, schools within Penn, and their selection probability by major type. Majors (and their associated degrees and schools) were drawn with replacement and randomized to resumes after subjects selected to view either Humanities & Social Sciences resumes or STEM resumes.

A.2.5 Components from Real Resumes

For work experiences, leadership experiences, and skills, we drew on components of resumes of real Penn students. This design choice improved the realism of the study by matching the tone and content of real Penn job seekers. Moreover, it improved the validity of our results by ensuring that our distribution of resume characteristics — and resume quality more broadly — was close to the true distribution of Penn students.

Source resumes came from campus databases (e.g., student club resume books) and from seniors who submitted their resumes in order to participate in the matching process. When submitting resumes, students were informed that components of their resumes could be shown directly to employers. We scraped these resumes using a commercial resume parser (the Sovren Parser). From the scraped data, we compiled one list with collections of skills, and a second list of experiences comprising an organization or employer, a position title, a location, and a job description (generally in the form of resume bullet points).

Resume components were selected to be interchangeable across resumes. To that end, we cleaned work experiences, leadership experiences, and skills lists in the following ways:

- Removed any information that might indicate gender, race, or religion (e.g., "Penn Women's Varsity Fencing Team" was changed to "Penn Varsity Fencing Team" and "Penn Muslim Students Association" was not used)
- Screened out components indicative of a specific major (e.g., "Exploratory Biochemistry Intern" was not used)
- Corrected grammatical errors

Work Experience — We designed our resumes to vary both the quality and quantity of work experience. All resumes had a work experience during the summer before the candidate's senior year (June–August 2017). This work experience was either a regular internship (20/40) or a top internship (20/40). In addition, some resumes also had a second work experience (26/40), which varied in quality between a work-for-money job (13/40) or a regular internship (13/40). The job title, employer, description, and location shown on the hypothetical resumes were the same as in the source resume, with the minimal cleaning described above.

Before selecting the work experiences, we defined a *Top Internship* to be a substantive position at a prestigious employer. We chose this definition both to identify prestigious firms and to distinguish between different types of jobs at those firms, such as a barista at a local Starbucks and a marketing intern at Starbucks headquarters. We identified a prestigious employer to be one of the 50 firms hiring the most Penn graduates in 2014 (as compiled by our Career Services partners). Since experiences at these firms were much more common among Humanities & Social Sciences majors, we supplemented this list with 39 additional firms hiring most often from Penn's School of Engineering and Applied Science. We extracted experiences at these firms from our full list of scraped experiences, and selected a total of 40 *Top Internship* experiences, with 20 coming from resumes of Humanities & Social Sciences majors and 20 from resumes of STEM majors. All of these *Top Internship* experiences had to be believably interchangeable within a major category. These internships included positions at Bain Capital, Goldman Sachs, Morgan Stanley, Northrop Grumman, Boeing Company, and Google (see Table A.4 for a complete list). This variation identified the variable *Top Internship* in our analysis, which is measured relative to having a regular internship (since all resumes had some job in this position).

Table A.4—Top Internship Employers

Humanities & Social Sciences	**STEM**
Accenture plc	Accenture
Bain Capital Credit	Air Products and Chemicals, Inc
Bank of America Merrill Lynch	Bain & Company
Comcast Corporation	Boeing Company
Deloitte Corporate Finance	Credit Suisse Securities (USA) LLC
Ernst & Young U.S. LLP	Deloitte
Goldman Sachs	Epic Systems
IBM	Ernst & Young
McKinsey & Company	Federal Reserve Bank of New York
Morgan Stanley	Google
PricewaterhouseCoopers	J.P. Morgan
UBS Financial Services Inc.	McKinsey & Company
	Microsoft
	Morgan Stanley Wealth Management
	Northrop Grumman Aerospace Systems
	Palantir Technologies
	Pfizer Inc
	PricewaterhouseCoopers, LLP

Employers of top internships in Humanities & Social Sciences and STEM. A total of 20 *Top Internship* positions were used for each major type; some employers were used multiple times, when they appeared on multiple source resumes. Each firm name was used as provided on the source resume, and may not reflect the firm's official name. The names of some repeat *Top Internship* employers were provided differently on different source resumes (e.g., "Ernst & Young U.S. LLP" and "Ernst & Young"); in this case, we retained the name from the source resume associated with the internship.

We selected 33 regular internships separately for the two major groups: 20 regular internships for randomization in the first work experience position, and 13 for the second position. Regular internships had few restrictions, but could not include employment at the firms associated with top internships, and could not include work-for-money job titles (described below and shown in Table A.5). All jobs had to be believably interchangeable within major category. The regular internships in the second job position (the summer after sophomore year) defined the variable *Second Internship*, and is measured relative to having no job in the second work experience position. Our dynamically generated resumes automatically adjusted in length when no second job was selected, in order to avoid a large gap on the page.

The remaining 13 jobs in the second work position were identified as *Work for Money*. We identified these positions in the real resume components by compiling a list of job titles and phrases that we thought would be typical in this category, such as Cashier, Barista, and Waiter or Waitress (see Table A.5 Columns 2–4 for the full list). We extracted components in our full list of scraped experiences that matched these search terms, and selected 13 that could be plausibly interchangeable across any major. During randomization, these 13 jobs were used for both Humanities & Social Sciences and STEM majors. The first column of Table A.5 shows the job titles that appeared as *Work for Money* jobs in our hypothetical resumes. Columns 2–4 provide the list of job titles used for identifying work-for-money jobs in the scraped data, and for matching candidates to employer preferences.

Leadership Experience — We defined leadership experiences to be those resume components that indicated membership or participation in a group, club, volunteer organization, fraternity/sorority, or student government. We selected leadership experiences from our full list of scraped experience components, requiring that the positions be clearly non-employment, include a position title, organization, and description, and be plausibly interchangeable across gender, race, and major type. While many real resumes simply identified a position title and organization, we required that the components for our hypothetical resumes include a description of the activity for use as bullet points. We curated a list of 80 leadership experiences to use for both Humanities & Social Sciences and STEM resumes. Each resume included two randomly selected leadership experiences. We used the same leadership positions for both major types under the assumption that most extracurricular activities at Penn could plausibly include students from all majors; however, this required us to exclude the few leadership experiences that were too revealing of field of study (e.g., "American Institute of Chemical Engineers").

Every leadership position was assigned to the location of Penn's campus, Philadelphia, PA. This was done for consistency and believability, even if some of the leadership positions were held in other locations in the source resume. We randomly selected two ranges of years during a student's career to assign to the experiences, and we ordered the experiences chronologically on the hypothetical resume based on the end year of the experience.

Skills — We selected 40 skill sets from Humanities & Social Sciences resumes and 40 from STEM resumes for randomization in the survey tool. We intended for these skill sets to accurately reflect the types of skills common in the resumes we collected, and to be plausibly interchangeable within a major type. For randomization, skill sets were drawn from within a major type. To induce variation for the variable *Technical Skills*, we randomly upgraded a skill set with probability 25% by adding two skills from the set of programming languages {Ruby, Python, PHP, Perl} and two skills from the set of statistical programming packages {SAS, R, Stata, Matlab} in random order. To execute this randomization, we removed any other references to these eight languages from the skill sets. Many source resumes display skills in

Table A.5—Work for Money Job Titles & Identifying Phrases

Used for Resume Tool	**Used for Identifying Components & Matching**		
Assistant Shift Manager	Assistant coach	Courier	Phone Bank
Barista	Attendant	Custodian	Prep Cook
Cashier	Babysitter	Customer Service	Receptionist
Front Desk Staff	Backroom Employee	Dishwasher	Retail Associate
Host & Cashier	Bag Boy	Doorman	Rug Flipper
Sales Associate	Bagger	Driver	Sales Associate
Salesperson, Cashier	Bank Teller	Employee	Sales Representative
Server	Barback	Front Desk	Salesman
	Barista	Fundraiser	Salesperson
	Bartender	Gardener	Saleswoman
	Bellhop	Host	Server
	Bodyguard	Hostess	Shift Manager
	Bookseller	House Painter	Stock boy
	Bouncer	Instructor	Stockroom
	Bus boy	Janitor	Store Employee
	Busser	Laborer	Temp
	Caddie	Landscaper	Tour Guide
	Caddy	Librarian	Trainer
	Call center	Lifeguard	Tutor
	Canvasser	Line Cook	Valet
	Cashier	Maid	Vendor
	Caterer	Messenger	Waiter
	Cleaner	Mover	Waitress
	Clerk	Nanny	Work Study
	Counselor	Petsitter	Worker

Position titles and relevant phrases used to identify work for money in hypothetical resumes for evaluation and in candidate pool resumes. The first column contains the eight unique positions randomized into hypothetical resumes; position titles Cashier, Barista, Sales Associate, and Server were used more than once and associated with different firms. Columns 2–4 specify the work-for-money positions used to predict hiring interest of potential candidates from the pool of prospective matches. Any position title containing one of these phrases was identified as work for money for the purposes of matching.

list format, with the word "and" coming before the final skill; we removed the "and" to make the addition of *Technical Skills* more natural.

A.3 Matching Appendix

A.3.1 Students

To identify job seekers, the career services office sent an email to seniors offering "an opportunity to reach more employers" by participating in our pilot study, to be run in parallel with all existing recruiting activities. The full student recruitment email is reproduced in Appendix A.2. After uploading a resume and answering basic questions on their industry and locations of interest, students were entered into the applicant pool, and we did not contact them again. If matched with an employer, we emailed the student's resume to the employer and encouraged the employer to contact the student directly. Students received no other incentive for participating.

A.3.2 Matches with Job Seekers

To match job-seeking students with the recruiters in our study, we parsed the student resumes and coded their content into variables describing the candidate's education, work experience, and leadership experience, using a combination of parsing software and manual transcription. We did not include any measure of ethnicity or gender in providing matches, nor did we take into account any employer's revealed ethnic or gender preferences. The full list of variables used for matching is shown in Table A.6.

We ran individual ridge regressions for each completed firm-position survey, merging the responses of multiple recruiters in a company if recruiting for the same position. We ran separate regressions using the hiring interest rating (the response to the question "How interested would you be in hiring **[Name]**?") and the likelihood of acceptance (the response to the question "How likely do you think **[Name]** would be to accept a job with your organization?") as outcome variables. We used cross-validation to select the punishment parameter of the ridge regression by running pooled regressions with a randomly selected hold-out sample, and identifying the punishment parameter that minimized prediction error in the hold-out sample. Repeating this process with 100 randomly selected hold-out samples separately for Humanities & Social Sciences and STEM employers, we use the average of the best-performing punishment parameters as the punishment parameter for the individual regressions. Based on the individual regression results, we then generated out-of-sample predictions of hiring interest and likelihood of acceptance for the resumes in our match pool that met minimal matching requirements for industry and geographic location. Finally, we generated a "callback index" as a weighted average of the predicted hiring interest and likelihood of acceptance (callback $= \frac{2}{3}$hiring interest $+ \frac{1}{3}$likelihood of acceptance). The 10 resumes with the highest callback indices for each employer were selected as matches.

We emailed each employer a zipped file of these matches (i.e., 10 resumes in PDF format). If multiple recruiters from one firm completed the tool for one hiring

Table A.6—Candidate Matching Variables

Variable	**Definition**
GPA	Overall GPA, if available. If missing, assign lowest GPA observed in the match pool
Engineering	Indicator for Computer Sciences, Engineering, or Math majors (for STEM candidates)
Humanities	Indicator for Humanities majors (for Humanities & Social Sciences Candidates)
Job Count	Linear variable for 1, 2, or 3+ work experiences.
Top Firm	Resume has a work experience at one of the firms hiring the most Penn graduates
Major City	Resume has a work experience in New York, San Francisco, Chicago, or Boston
Work for Money	Resume has a job title including identifying phrase from Table A.5
S&P500 or Fortune 500	Resume has an experience at an S&P 500 or Fortune 500 firm
Leader	Resume has a leadership position as Captain, President, Chair, Chairman, or Chairperson

Variables used to identify individual preferences and recommend matched candidates. Variables were identified in hypothetical resumes and in the candidate resume pool. Subjects were provided with 10 real job seekers from Penn whose qualifications matched their preferences based on predictions from a ridge regression with these features.

position, we combined their preferences and provided a single set of 10 resumes to the group.[37] This set of candidate resumes was the only incentive for participating in the study.

[37]In cases where multiple recruiters from a firm completed the tool in order to fill different positions, or where a single recruiter completed multiple times for different positions, we treated these as unique completions and provided them with 10 candidate resumes for each position.

B Results Appendix

In this section, we describe additional results and report on robustness checks run to validate our main results. In Section B.1, we show additional analysis related to our main human capital results. In Section B.2, we verify our results after reweighting observations to the true distribution of GPAs in actual Penn student resumes. In Section B.3, we discuss preferences throughout the quality distribution. In Section B.4, we provide additional results on candidate demographics. In Section B.5, we discuss the relationship between *Likelihood of Acceptance* and *Hiring Interest*.

B.1 Additional Results on Human Capital

The human capital results in Section B rely on the independent randomization of work experiences and other resume elements. This randomization leads to some combinations of resume elements that are unlikely to arise in practice, despite drawing each variable from a realistic univariate distribution. If employers value a set of experiences that form a cohesive narrative, independent randomization could lead to strange relationships in our data. If employers value combinations of work experiences, narrative might be an omitted variable that could introduce bias (e.g., if our *Top Internships* are more likely to generate narratives than regular internships, we may misestimate their effect on hiring interest). In Table B.1, we address this concern by showing that the cross-randomization of work experiences does not drive our results. To test this, we had three undergraduate research assistants at the University of Pennsylvania rate all possible combinations of work experiences that could have appeared on our hypothetical resumes.[38] We used their responses to create a dummy—denoted *Narrative*—that is equal to 1 when a resume has a work experience in the summer before junior year that is related to the work experience before senior year, and 0 otherwise. As a result of this process, we identified that 17.5% of the realized resumes in our study (i.e., those resumes actually shown to subjects) had a cohesive work experience narrative. None of these resumes included *Work for Money* because our RA raters did not see these jobs as contributing to a narrative. Appendix Table B.1 runs the same regressions as Table 2 but additionally controls for *Narrative*. All results from Table 2 remain similar in size and statistical significance.

In Table B.2, we estimate the value of degrees from more prestigious schools within Penn. We replace the major fixed effects of Table 2 with binary variables for *School of Engineering and Applied Science* and *Wharton*, as well as a binary control for whether the subject has chosen to review Humanities & Social Sciences or STEM

[38]As Penn students, these RAs were familiar with the type of work experiences Penn students typically have in the summers before their junior and senior years. Blind to our results, each RA rated 1040 combinations (40 work experiences in the summer before senior year $\times$ 26 work experiences in the summer before junior year) for Humanities & Social Sciences majors, and another 1040 combinations (40×26) for the STEM majors. They rated each combination on the extent to which the two work experiences had a cohesive narrative on a scale of 1 to 3 where 1 indicated "These two jobs are not at all related," 2 indicated "These two jobs are somewhat related," and 3 indicated "These two jobs are very related." The majority of combinations received a rating of 1 so we introduce a binary variable *Narrative* equal to 1 if the jobs were rated as somewhat or very related, and 0 if the jobs were not at all related.

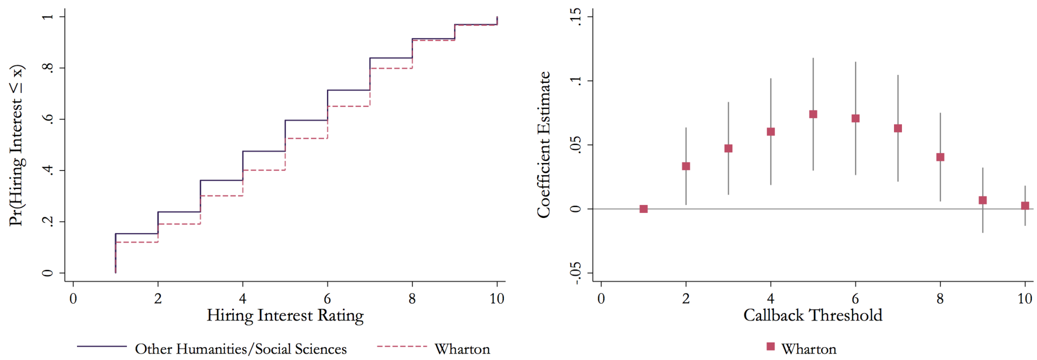
Table B.1—Work Experience Narrative

	Dependent Variable: Hiring Interest				
	OLS	OLS	OLS	GPA-Scaled OLS	Ordered Probit
GPA	2.128	2.194	2.200	1.000	0.892
	(0.145)	(0.150)	(0.129)	(.)	(0.061)
Top Internship	0.896	0.892	0.888	0.404	0.375
	(0.095)	(0.099)	(0.081)	(0.043)	(0.040)
Second Internship	0.349	0.364	0.319	0.145	0.156
	(0.142)	(0.150)	(0.122)	(0.056)	(0.059)
Work for Money	0.115	0.160	0.157	0.071	0.052
	(0.110)	(0.114)	(0.091)	(0.042)	(0.047)
Technical Skills	0.042	0.049	-0.076	-0.034	0.010
	(0.104)	(0.108)	(0.090)	(0.041)	(0.044)
Female, White	-0.149	-0.213	-0.159	-0.072	-0.060
	(0.114)	(0.118)	(0.096)	(0.044)	(0.048)
Male, Non-White	-0.174	-0.181	-0.175	-0.079	-0.076
	(0.137)	(0.142)	(0.115)	(0.052)	(0.057)
Female, Non-White	-0.011	-0.024	0.026	0.012	-0.015
	(0.137)	(0.144)	(0.120)	(0.055)	(0.058)
Narrative	0.214	0.237	0.278	0.126	0.093
	(0.165)	(0.175)	(0.144)	(0.066)	(0.068)
Observations	2880	2880	2880	2880	2880
R^2	0.130	0.181	0.484		
p-value for test of joint significance of Majors	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001
Major FEs	Yes	Yes	Yes	Yes	Yes
Leadership FEs	No	Yes	Yes	Yes	No
Order FEs	No	Yes	Yes	Yes	No
Subject FEs	No	No	Yes	Yes	No

Ordered probit cutpoints: 1.91, 2.28, 2.64, 2.94, 3.26, 3.6, 4.05, 4.52, and 5.03.

Table shows OLS and ordered probit regressions of hiring interest from Equation (1), with an additional control for *Narrative*. Robust standard errors are reported in parentheses. *GPA*; *Top Internship*; *Second Internship*; *Work for Money*; *Technical Skills*; *Female, White*; *Male, Non-White*; *Female, Non-White* and major are characteristics of the hypothetical resume, constructed as described in Section C and in Appendix A.2. *Narrative* is a characteristic of resumes, defined as work experiences that are related in some way. Fixed effects for major, leadership experience, resume order, and subject included in some specifications as indicated. R^2 is indicated for each OLS regression. GPA-Scaled OLS presents the results of Column 3 divided by the Column 3 coefficient on GPA, with standard errors calculated by delta method. The p-value of a test of joint significance of major fixed effects is indicated (F-test for OLS regressions, likelihood ratio test for ordered probit regressions).

Figure B.1. : Wharton



(a) Empirical CDF

(b) Linear Probability Model

Empirical CDF of *Hiring Interest* (Panel (a)) and difference in counterfactual callback rates (Panel (b)) for *Wharton* and *Other Humanities & Social Sciences*. Empirical CDFs show the share of hypothetical candidate resumes with each characteristic with a *Hiring Interest* rating less than or equal to each value. The counterfactual callback plot shows the difference between groups in the share of candidates at or above the threshold—that is, the share of candidates who would be called back in a resume audit study if the callback threshold were set to any given value. 95% confidence intervals are calculated from a linear probability model with an indicator for being at or above a threshold as the dependent variable.

resumes (coefficients not reported).[39] We find that employers find degrees from these schools 0.4–0.5 Likert-scale points more desirable than degrees from Penn's College of Arts and Sciences. As shown in Figure B.1, and as discussed in Section C, we also investigate the effect of having a degree from Wharton across the distribution of hiring interest.

B.2 Re-weighting by GPA

In generating hypothetical resumes, we randomly selected candidate GPAs from $Unif[2.90, 4.00]$, rather than from the true distribution of GPAs among job seekers at Penn, which is shown in Figure B.2.[40] In this section, we demonstrate that this choice does not drive our results. In Tables B.3, B.4, and B.5, we rerun the regressions of Tables 2, 3, and 4 weighted to reflect the naturally occurring distribution of GPA among our Penn senior candidate pool (i.e., the job seekers used for matching, see Appendix A.3). We do not include missing GPAs in the reweighting, though our results are robust to re-weighting with missing GPAs treated as low GPAs.[41]

[39] Major fixed effects are perfectly multicollinear with the variables for school, since no two schools grant the same degrees in the same major.

[40] We parameterized *GPA* to be drawn $Unif[2.90, 4.00]$ to give us statistical power to test the importance of GPA on hiring interest, but this distribution is not exactly the distribution of GPA among Penn seniors engaging in on campus recruiting.

[41] Some students may strategically omit low GPAs from their resumes, and some resume formats were difficult for our resume parser to scrape.

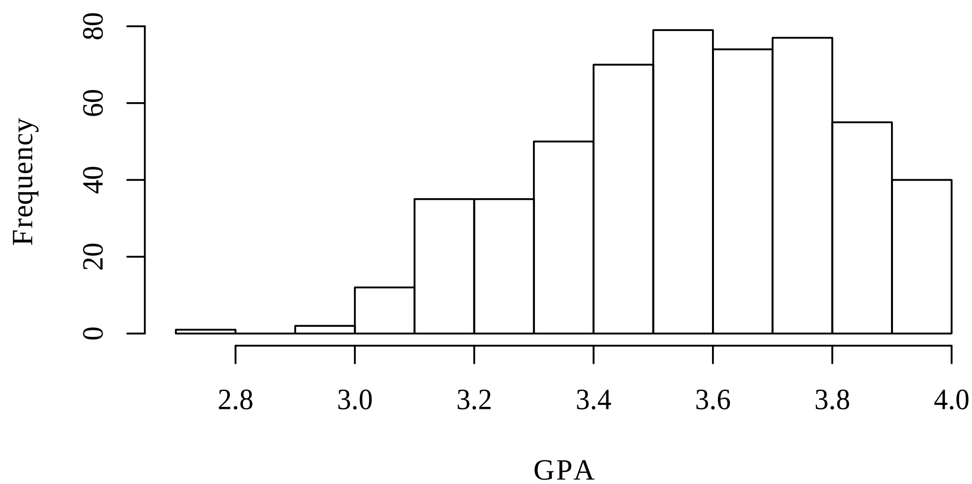
Table B.2—Prestigious Schools

	Dependent Variable: Hiring Interest				
	OLS	OLS	OLS	GPA-Scaled OLS	Ordered Probit
GPA	2.129	2.187	2.192	1.000	0.887
	(0.145)	(0.149)	(0.128)	(.)	(0.062)
Top Internship	0.908	0.913	0.905	0.413	0.378
	(0.094)	(0.098)	(0.080)	(0.043)	(0.039)
Second Internship	0.443	0.465	0.451	0.206	0.195
	(0.112)	(0.118)	(0.094)	(0.045)	(0.047)
Work for Money	0.108	0.141	0.143	0.065	0.049
	(0.110)	(0.113)	(0.092)	(0.042)	(0.046)
Technical Skills	0.038	0.040	-0.082	-0.037	0.009
	(0.103)	(0.107)	(0.090)	(0.041)	(0.043)
Female, White	-0.146	-0.207	-0.160	-0.073	-0.057
	(0.113)	(0.118)	(0.096)	(0.044)	(0.047)
Male, Non-White	-0.189	-0.196	-0.181	-0.083	-0.080
	(0.137)	(0.142)	(0.115)	(0.053)	(0.057)
Female, Non-White	-0.000	-0.011	0.037	0.017	-0.009
	(0.137)	(0.144)	(0.120)	(0.055)	(0.057)
School of Engineering	0.497	0.441	0.403	0.184	0.239
	(0.199)	(0.206)	(0.164)	(0.076)	(0.086)
Wharton	0.459	0.502	0.417	0.190	0.184
	(0.110)	(0.115)	(0.093)	(0.044)	(0.046)
Observations	2880	2880	2880	2880	2880
R^2	0.115	0.168	0.472		
Major FEs	No	No	No	Yes	No
Leadership FEs	No	Yes	Yes	Yes	No
Order FEs	No	Yes	Yes	Yes	No
Subject FEs	No	No	Yes	Yes	No

Ordered probit cutpoints: 2.48, 2.84, 3.20, 3.49, 3.81, 4.15, 4.60, 5.06, and 5.57.

Table shows OLS and ordered probit regressions of hiring interest from Equation (1), with effects for school, and a control for whether the employer selected to view Humanities & Social Sciences resumes or STEM resumes (coefficient not displayed). Robust standard errors are reported in parentheses. *GPA*; *Top Internship*; *Second Internship*; *Work for Money*; *Technical Skills*; *Female, White*; *Male, Non-White*; *Female, Non-White* and major are characteristics of the hypothetical resume, constructed as described in Section C and in Appendix A.2. *School of Engineering* indicates a resume with a degree from Penn's School of Engineering and Applied Sciences; *Wharton* indicates a resume with a degree from the Wharton School. Fixed effects for major, leadership experience, resume order, and subject included in some specifications as indicated. GPA-Scaled OLS presents the results of Column 3 divided by the Column 3 coefficient on GPA, with standard errors calculated by delta method. R^2 is indicated for each OLS regression.

Figure B.2. : Distribution of GPA Among Scraped Resumes



Histogram representing the distribution of GPA among scraped resumes in our candidate matching pool. Distribution excludes any resumes for which GPA was not available (e.g., resume did not list GPA, resume listed only GPA within concentration, or parser failed to scrape). GPAs of participating Penn seniors may not represent the GPA distribution at Penn as a whole.

These regressions confirm the results of Tables 2, 3, and 4 in direction and statistical significance.

Matching the underlying distribution of characteristics in hypothetical resumes to the distribution of real candidates is also an issue for resume auditors who must contend with a limited number of underlying resumes (i.e., resumes that they manipulate to create treatment variation). Given uncertainty about the characteristics of candidates and the limited number of underlying resumes, resume auditors may not be able to perfectly match the distribution of characteristics of a target population. An additional advantage of the IRR methodology is that it involves collecting a large number of resumes from an applicant pool of real job seekers, which gives us information on the distribution of candidate characteristics that we can use to re-weight the data ex post.

Table B.3—Human Capital Experience—Weighted by GPA

	Dependent Variable: Hiring Interest				
	OLS	OLS	OLS	GPA-Scaled OLS	Ordered Probit
GPA	2.274	2.339	2.320	1.000	0.963
	(0.175)	(0.168)	(0.146)	(.)	(0.079)
Top Internship	0.831	0.832	0.862	0.372	0.353
	(0.110)	(0.109)	(0.088)	(0.043)	(0.047)
Second Internship	0.488	0.482	0.513	0.221	0.216
	(0.129)	(0.130)	(0.105)	(0.047)	(0.054)
Work for Money	0.178	0.193	0.199	0.086	0.075
	(0.129)	(0.125)	(0.100)	(0.044)	(0.056)
Technical Skills	0.077	0.039	-0.106	-0.046	0.022
	(0.118)	(0.119)	(0.102)	(0.044)	(0.051)
Female, White	-0.057	-0.099	-0.038	-0.016	-0.021
	(0.134)	(0.130)	(0.105)	(0.045)	(0.057)
Male, Non-White	-0.239	-0.181	-0.111	-0.048	-0.097
	(0.154)	(0.154)	(0.123)	(0.053)	(0.066)
Female, Non-White	-0.020	-0.032	0.040	0.017	-0.017
	(0.166)	(0.162)	(0.134)	(0.058)	(0.071)
Observations	2880	2880	2880	2880	2880
R^2	0.146	0.224	0.505		
p-value for test of joint significance of Majors	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001
Major FEs	Yes	Yes	Yes	Yes	Yes
Leadership FEs	No	Yes	Yes	Yes	No
Order FEs	No	Yes	Yes	Yes	No
Subject FEs	No	No	Yes	Yes	No

Ordered probit cutpoints: 2.30, 2.71, 3.04, 3.34, 3.66, 3.99, 4.49, 4.95, and 5.46.

Table shows OLS and ordered probit regressions of *Hiring Interest* from Equation (1), weighted by the distribution of GPA in resumes in the candidate matching pool. Robust standard errors are reported in parentheses. *GPA*; *Top Internship*; *Second Internship*; *Work for Money*; *Technical Skills*; *Female, White*; *Male, Non-White*; *Female, Non-White* and major are characteristics of the hypothetical resume, constructed as described in Section C and in Appendix A.2. Fixed effects for major, leadership experience, resume order, and subject included in some specifications as indicated. R^2 is indicated for each OLS regression. GPA-Scaled OLS presents the results of Column 3 divided by the Column 3 coefficient on GPA, with standard errors calculated by delta method. The p-value of a test of joint significance of major fixed effects is indicated for each model (F-test for OLS regressions, likelihood ratio test for ordered probit regression).

Table B.4—Human Capital Experience by Major Type—Weighted by GPA

	Dependent Variable: Hiring Interest									
	Humanities & Social Sciences					STEM				
	OLS	OLS	OLS	GPA-Scaled OLS	Ordered Probit	OLS	OLS	OLS	GPA-Scaled OLS	Ordered Probit
GPA	2.365	2.452	2.476	1.000	1.008	2.028	2.187	2.000	1.000	0.848
	(0.212)	(0.198)	(0.172)	(.)	(0.096)	(0.306)	(0.325)	(0.266)	(.)	(0.133)
Top Internship	0.973	0.941	0.982	0.397	0.412	0.448	0.526	0.581	0.291	0.204
	(0.127)	(0.125)	(0.102)	(0.049)	(0.056)	(0.218)	(0.222)	(0.182)	(0.101)	(0.093)
Second Internship	0.476	0.384	0.494	0.199	0.217	0.529	0.496	0.383	0.192	0.223
	(0.153)	(0.155)	(0.125)	(0.052)	(0.065)	(0.235)	(0.252)	(0.199)	(0.103)	(0.102)
Work for Money	0.091	0.035	0.086	0.035	0.037	0.387	0.459	0.517	0.259	0.182
	(0.152)	(0.145)	(0.118)	(0.048)	(0.065)	(0.247)	(0.270)	(0.201)	(0.106)	(0.106)
Technical Skills	0.089	0.026	-0.146	-0.059	0.026	0.011	-0.059	-0.093	-0.046	0.005
	(0.142)	(0.142)	(0.120)	(0.048)	(0.061)	(0.217)	(0.240)	(0.193)	(0.096)	(0.093)
Female, White	0.110	0.036	0.110	0.044	0.048	-0.460	-0.637	-0.658	-0.329	-0.183
	(0.159)	(0.153)	(0.125)	(0.051)	(0.068)	(0.251)	(0.253)	(0.206)	(0.110)	(0.107)
Male, Non-White	-0.033	0.037	0.038	0.015	-0.006	-0.799	-0.704	-0.590	-0.295	-0.352
	(0.181)	(0.183)	(0.147)	(0.059)	(0.077)	(0.295)	(0.322)	(0.260)	(0.129)	(0.130)
Female, Non-White	0.036	0.024	0.078	0.032	0.001	-0.180	0.014	0.039	0.020	-0.074
	(0.189)	(0.186)	(0.154)	(0.062)	(0.082)	(0.332)	(0.318)	(0.264)	(0.132)	(0.140)
Observations	2040	2040	2040	2040	2040	840	840	840	840	840
R^2	0.141	0.242	0.522			0.150	0.408	0.644		
p-value for test of joint significance of Majors	0.105	0.152	0.022	0.022	0.138	< 0.001	0.003	< 0.001	< 0.001	< 0.001
Major FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Leadership FEs	No	Yes	Yes	Yes	No	No	Yes	Yes	Yes	No
Order FEs	No	Yes	Yes	Yes	No	No	Yes	Yes	Yes	No
Subject FEs	No	No	Yes	Yes	No	No	No	Yes	Yes	No

Ordered probit cutpoints (Column 5): 2.54, 2.89, 3.23, 3.54, 3.86, 4.20, 4.71, 5.18, 5.70.

Ordered probit cutpoints (Column 10): 1.78, 2.31, 2.62, 2.89, 3.20, 3.51, 3.98, 4.44, 4.92.

Table shows OLS and ordered probit regressions of *Hiring Interest* from Equation (1). *GPA*; *Top Internship*; *Second Internship*; *Work for Money*; *Technical Skills*; *Female, White*; *Male, Non-White*; *Female, Non-White* and major are characteristics of the hypothetical resume, constructed as described in Section C and in Appendix A.2. Fixed effects for major, leadership experience, resume order, and subject included as indicated. R^2 is indicated for each OLS regression. GPA-Scaled OLS columns present the results of Column 3 and Column 8 divided by the Column 3 and Column 8 coefficient on GPA, with standard errors calculated by delta method. The p-values of tests of joint significance of major fixed effects and demographic variables are indicated (F-test for OLS, likelihood ratio test for ordered probit) after a Bonferroni correction for analyzing two subgroups.

B.3 Distributional Appendix

As discussed in Section C, average preferences for candidate characteristics might differ from the preferences observed in the tails. The stylized example in Figure B.3 shows this concern graphically. Imagine the light (green) distribution shows the expected productivity—based on the content of their resumes—of undergraduate research assistants (RAs) majoring in Economics at the University of Pennsylvania and the dark (gray) distribution shows the expected productivity of undergraduate RAs enrolled at the Wharton School. In this example, the mean Wharton student would make a less productive RA, reflecting a lack of interest in academic research relative to business on average; however, the tails of the Wharton distribution are fatter, reflecting the fact that admission into Wharton is more selective, so a Wharton student who has evidence of research interest on her resume is expected to be better than an Economics student with an otherwise identical resume. Looking across the panels in Figure B.3, we see that as callback thresholds shift from being high (panel (a), where professors are very selective, only calling back around 8% of resumes) to medium (panel (b), where professors are calling back around 16% of resumes) to low (panel (c), where professors are calling back around 28% of resumes), a researcher conducting a resume audit study might conclude that there is an advantage on the RA market of being at Wharton, no effect, or a disadvantage.[42]

A researcher might particularly care about how employers respond to candidate characteristics around the empirically observed threshold (e.g., the researcher may be particularly interested in how employers respond to candidates in a particular market, with a particular level of selectivity, at a particular point in time). Nevertheless, there are a number of reasons why richer information about the underlying distribution of employer preferences for characteristics would be valuable for a researcher to uncover. A researcher might want to know how sensitive estimates are to: (1) an economic expansion or contraction that changes firms' hiring needs or (2) new technologies, such as video conferencing, which may change the callback threshold by changing the costs of interviewing. Similarly, a researcher may be interested in how candidate characteristics would affect callback in different markets (e.g., those known to be more or less selective) than the market where a resume audit was conducted. To conduct these counterfactual analyses, richer preference information would be valuable.

B.3.1 Comparing Results Across the Distribution

Resume audit studies often report differences in callback rates between two types of job candidates, either in a t-test or in a regression. However, as the overall callback rate becomes very large (i.e., almost all candidates get called back) or very small (i.e., few candidates get called back), the differences in callback rates tend toward zero. This is because, as discussed in footnote 22, the maximum possible difference in callback rates is capped by the overall callback rate.

[42]This stylized example uses two normal distributions. In settings where distributions are less well-behaved, the difference in callback rates might be even more sensitive to specific thresholds chosen.

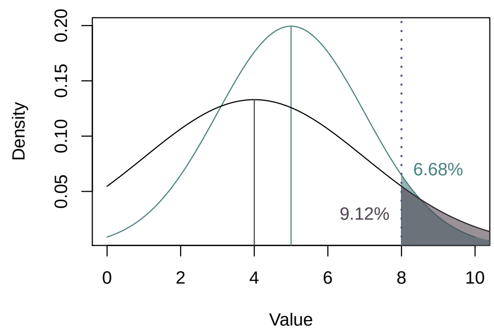
Table B.5—Likelihood of Acceptance—Weighted by GPA

	Dependent Variable: Likelihood of Acceptance			
	OLS	OLS	OLS	Ordered Probit
GPA	0.545	0.552	0.663	0.246
	(0.174)	(0.168)	(0.132)	(0.074)
Top Internship	0.725	0.709	0.694	0.299
	(0.111)	(0.108)	(0.083)	(0.047)
Second Internship	0.524	0.456	0.432	0.220
	(0.132)	(0.133)	(0.101)	(0.056)
Work for Money	0.205	0.150	0.185	0.087
	(0.128)	(0.125)	(0.098)	(0.054)
Technical Skills	0.041	-0.039	-0.114	0.012
	(0.120)	(0.120)	(0.097)	(0.050)
Female, White	-0.209	-0.276	-0.224	-0.083
	(0.135)	(0.133)	(0.103)	(0.057)
Male, Non-White	-0.248	-0.273	-0.114	-0.113
	(0.157)	(0.155)	(0.120)	(0.066)
Female, Non-White	-0.174	-0.224	-0.155	-0.086
	(0.160)	(0.156)	(0.124)	(0.068)
Observations	2880	2880	2880	2880
R^2	0.077	0.162	0.509	
p-value for test of joint significance of Majors	< 0.001	< 0.001	< 0.001	< 0.001
Major FEs	Yes	Yes	Yes	Yes
Leadership FEs	No	Yes	Yes	No
Order FEs	No	Yes	Yes	No
Subject FEs	No	No	Yes	No

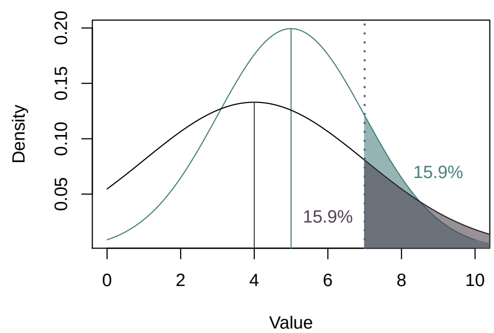
Ordered probit cutpoints: -0.09, 0.29, 0.64, 0.90, 1.26, 1.67, 2.13, 2.65, and 3.02.

Table shows OLS and ordered probit regressions of *Likelihood of Acceptance* from Equation (1), weighted by the distribution of GPA in resumes in our candidate matching pool. Robust standard errors are reported in parentheses. *GPA*; *Top Internship*; *Second Internship*; *Work for Money*; *Technical Skills*; *Female, White*; *Male, Non-White*; *Female, Non-White* are characteristics of the hypothetical resume, constructed as described in Section C and in Appendix A.2. Fixed effects for major, leadership experience, resume order, and subject included in some specifications as indicated. R^2 is indicated for each OLS regression. The p-value of a test of joint significance of major fixed effects is indicated (F-test for OLS regressions, likelihood ratio test for ordered probit regression).

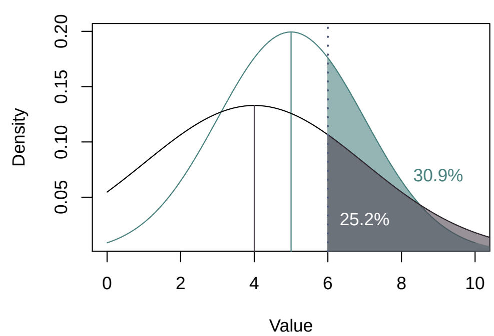
Figure B.3. : Callback Thresholds Example



(a) High Threshold



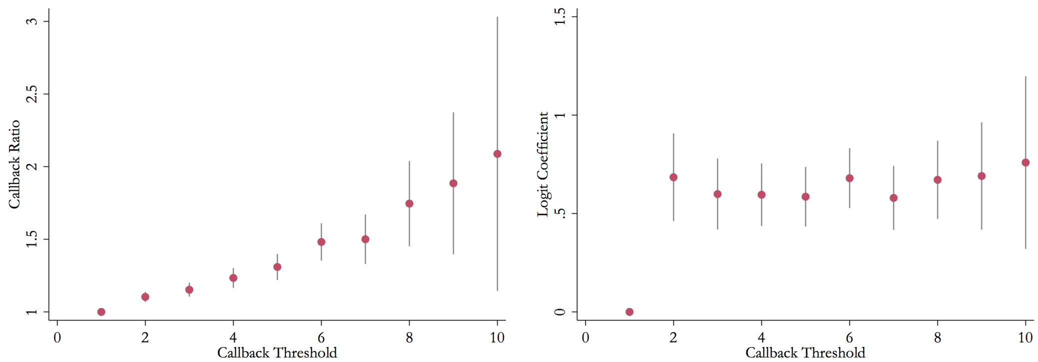
(b) Medium Threshold



(c) Low Threshold

A stylized example where average preferences differ from preferences at the upper tail. The distribution in green has a higher mean and lower variance, leading to thinner tails; the distribution in gray has a lower mean but higher variance, leading to more mass in the upper tail. As the callback threshold decreases from Panel (a) to Panel (c), the share of candidates above the threshold from each distribution changes. Estimating preferences from callbacks following this type of threshold process might lead to spurious conclusions.

Figure B.4. : Alternative Specifications: Top Internship



(a) Callback Ratio

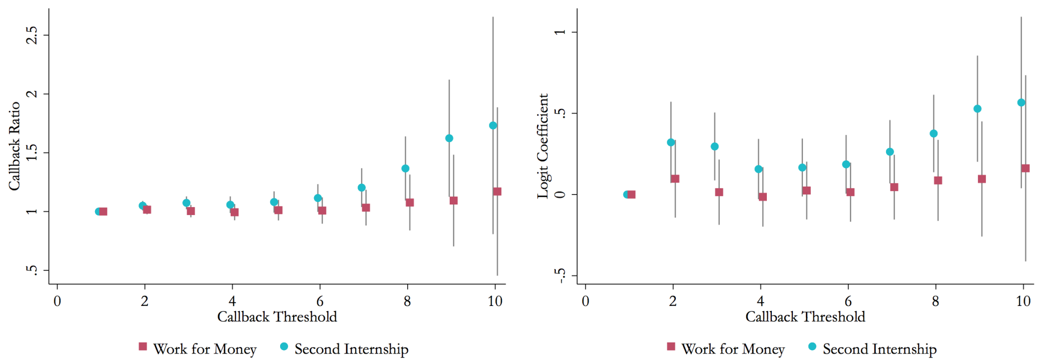
(b) Logit

Counterfactual callback ratios (Panel (a)) and counterfactual logit coefficients (Panel (b)) for *Top Internship*. Counterfactual callback is an indicator for each value of *Hiring Interest* equal to 1 if *Hiring Interest* is greater than or equal to the value, and 0 otherwise. Callback ratio is defined as the counterfactual callback rate for candidates with the characteristic divided by the counterfactual callback rate for candidates without. 95% confidence intervals are calculated from a linear probability model using the delta method. Logit coefficients are estimated from a logit regression with counterfactual callback as the dependent variable.

This is not a threat to the internal validity of most resume audit studies executed in a single hiring environment. However, this can cause problems when comparing across studies, or within a study run in different environments. For example, if one wanted to show that there was less racial discrimination in one city versus another, and the underlying callback rates in those cities differed, an interaction between city and race may be difficult to interpret. Note that such an exercise is performed in Kroft et al. (2013) to compare the response to unemployment in cities with high unemployment (and likely low overall callback rates) versus cities with low unemployment rates (and high callback rates). In that particular study, the "bias" caused by comparing across different callback rates does not undermine the finding that employers in high unemployment rate cities respond less to unemployment spells. Nonetheless, researchers should use caution when implementing similar study designs.

In Figures B.4 and B.5, we look at how two different ways of measuring callback differences perform across the distribution (to contrast with the linear probability model). The lefthand side of each figure shows the ratio of the callback rates, another common way of reporting resume audit study results. For the positive effects in our study, this odds ratio tends to be larger at the upper tail, where a small difference in callbacks can result in a large response in the ratio. On the righthand side of each figure, we show effects estimated from a logit specification. We find that in our data, the effects estimated in logistic regression tend to be flatter across the quality distribution.

Figure B.5. : Alternative Specifications: Second Job Type



(a) Callback Ratio

(b) Logit

Counterfactual callback ratios (Panel (a)) and counterfactual logit coefficients (Panel (b)) for *Work for Money* and *Second Internship*. Counterfactual callback is an indicator for each value of *Hiring Interest* equal to 1 if *Hiring Interest* is greater than or equal to the value, and 0 otherwise. Callback ratio is defined as the counterfactual callback rate for candidates with the characteristic divided by the counterfactual callback rate for candidates without. 95% confidence intervals are calculated from a linear probability model using the delta method. Logit coefficients are estimated from a logit regression with counterfactual callback as the dependent variable.

B.4 Candidate Demographics Appendix

In this section, we provide additional analyses for our main results on candidate demographics. In B.4.1, we analyze our findings by the demographics of employers evaluating resumes. In B.4.2 we describe a test for implicit bias. In B.4.3, we discuss differential returns to quality by demographic group.

B.4.1 Rater Demographics

IRR allows us to collect information about the specific individuals rating resumes at the hiring firm. In Table B.6 we explore our main results by rater gender and race. White and female raters appear more likely to discriminate against male, non-white candidates than non-white or female raters.

B.4.2 Test for Implicit Bias

We leverage a feature of implicit bias—that it is more likely to arise when decision makers are fatigued (Wigboldus et al., 2004; Govorun and Payne, 2006; Sherman et al., 2004)—to test whether our data are consistent with implicit bias. Appendix Table B.7 investigates how employers respond to resumes in the first and second half of the study and to resumes before and after the period breaks—after every 10

Table B.6—Hiring Interest by Rater Demographics

	Dependent Variable: Hiring Interest	Rater Gender		Rater Race	
	All	Female Raters	Male Raters	Non-White Raters	White Raters
GPA	2.196	2.357	2.092	2.187	2.131
	(0.129)	(0.170)	(0.212)	(0.378)	(0.146)
Top Internship	0.897	0.726	1.139	1.404	0.766
	(0.081)	(0.105)	(0.140)	(0.234)	(0.091)
Second Internship	0.466	0.621	0.195	0.636	0.459
	(0.095)	(0.126)	(0.154)	(0.273)	(0.107)
Work for Money	0.154	0.303	-0.082	-0.124	0.192
	(0.091)	(0.120)	(0.156)	(0.255)	(0.104)
Technical Skills	-0.071	-0.079	-0.020	-0.123	-0.016
	(0.090)	(0.122)	(0.151)	(0.231)	(0.104)
Female, White	-0.161	-0.202	-0.216	0.004	-0.209
	(0.096)	(0.128)	(0.165)	(0.265)	(0.109)
Male, Non-White	-0.169	-0.311	-0.105	0.119	-0.241
	(0.115)	(0.149)	(0.200)	(0.285)	(0.132)
Female, Non-White	0.028	0.001	-0.065	-0.124	0.097
	(0.120)	(0.159)	(0.202)	(0.325)	(0.137)
Observations	2880	1720	1160	600	2280
R^2	0.483	0.525	0.556	0.588	0.503
Major FEs	Yes	Yes	Yes	Yes	Yes
Leadership FEs	Yes	Yes	Yes	Yes	Yes
Order FEs	Yes	Yes	Yes	Yes	Yes
Subject FEs	Yes	Yes	Yes	Yes	Yes

OLS regressions of *Hiring Interest* on candidate characteristics by rater gender and race. Sample includes 29 male and 42 female subjects; 57 White and 15 non-White subjects. Robust standard errors are reported in parentheses. *GPA*; *Top Internship*; *Second Internship*; *Work for Money*; *Technical Skills*; *Female, White*; *Male, Non-White*; *Female, Non-White* are characteristics of the hypothetical resume, constructed as described in Section C and in Appendix A.2. R^2 is indicated for each OLS regression. Fixed effects for major, leadership experience, resume order, and subject included in some specifications as indicated.

resumes—that we built into the survey tool.[43] The first and second columns show that subjects spend less time evaluating each resume in the second half of the study and in the latter half of each block of 10 resumes, suggesting evidence of fatigue. The third column reports a statistically significant interaction on *Latter Half of Block* $\times$ *Not a White Male* of -0.385 Likert-scale points, equivalent to about 0.18 GPA points, suggesting more discrimination against candidates who are not white males in the latter half of each block of 10 resumes. The fourth column reports, however, that the bias in the second half of the study is not statistically significantly larger than the bias in the first half. These results provide suggestive, though not conclusive, evidence that the discrimination we detect may indeed be driven by implicit bias.

[43]As described in Section I, after every 10 resumes an employer completed, the employer was shown a simple webpage with an affirmation that gave them a short break (e.g., after the first 10 resumes it read: "You have rated 10 of 40 resumes. Keep up the good work!"). Research suggests that such "micro breaks" can have relatively large effects on focus and attention (Rzeszotarski et al., 2013), and so we compare bias in the early half and latter half of each block of 10 resumes under the assumption that employers might be more fatigued in the latter half of each block of 10 resumes.

Table B.7—Implicit Bias

	Dependent Variable: Response Time		Dependent Variable: Hiring Interest	
Latter Half of Block	-3.518		0.360	
	(0.613)		(0.137)	
Second Half of Study		-4.668		-0.142
		(0.598)		(0.138)
Not a White Male	-0.642	-0.648	0.069	-0.107
	(0.666)	(0.665)	(0.115)	(0.118)
Latter Half of Block × Not a White Male			-0.385	
			(0.165)	
Second Half of Study × Not a White Male				-0.022
				(0.166)
GPA	2.791	2.944	2.187	2.187
	(0.961)	(0.949)	(0.128)	(0.128)
Top Internship	-0.799	-0.638	0.905	0.904
	(0.622)	(0.620)	(0.080)	(0.080)
Second Internship	2.163	2.118	0.471	0.458
	(0.752)	(0.750)	(0.093)	(0.093)
Work for Money	1.850	1.813	0.154	0.140
	(0.741)	(0.740)	(0.091)	(0.091)
Technical Skills	0.881	0.892	-0.067	-0.078
	(0.715)	(0.713)	(0.089)	(0.089)
Observations	2880	2880	2880	2880
R^2	0.405	0.412	0.475	0.475
p-value for test of joint significance of Majors	< 0.001	< 0.001	< 0.001	< 0.001
Major FEs	Yes	Yes	Yes	Yes
Leadership FEs	Yes	Yes	Yes	Yes
Order FEs	No	No	No	No
Subject FEs	Yes	Yes	Yes	Yes

Regressions of *Response Time* and *Hiring Interest* on resume characteristics and resume order variables. The first and second columns show *Response Time* regressions; the third and fourth columns show *Hiring Interest* regressions. *Response Time* is defined as the number of seconds before page submission, Winsorized at the 95^{th} percentile (77.9 seconds). Mean of *Response Time*: 23.6 seconds. *GPA*, *Top Internship*, *Second Internship*, *Work for Money*, *Technical Skills*, and *Not a White Male* are characteristics of the hypothetical resume, constructed as described in Section C and in Appendix A.2. *Latter Half of Block* is an indicator variable for resumes shown among the last five resumes within a 10-resume block. *Second Half of Study* is an indicator variable for resumes shown among the last 20 resumes viewed by a subject. Fixed effects for subjects, majors, and leadership experience included in all specifications. R^2 is indicated for each OLS regression. The p-value of an F-test of joint significance of major fixed effects is indicated for all models.

B.4.3 Interaction of Demographics with Quality

Table B.8 shows that white males gain more from having a *Top Internship* than candidates who are not white males. White females receive the least credit for prestigious internships, garnering about 60% as much credit as white males. We speculate that this may be due to firms believing that prestigious internships are a less valuable signal of quality if the previous employer may have selected the candidate due to positive tastes for diversity. Figure B.6 looks at the relationship between *Top Internship* and being *Not a White Male* throughout the quality distribution. We find that when a candidate is of sufficiently high quality, a *Top Internship* is equally valuable for white male candidates and those who are not white males. This may suggest that other signals of quality may inoculate candidates from the assumption that an impressive work history is the result of diversity initiatives.

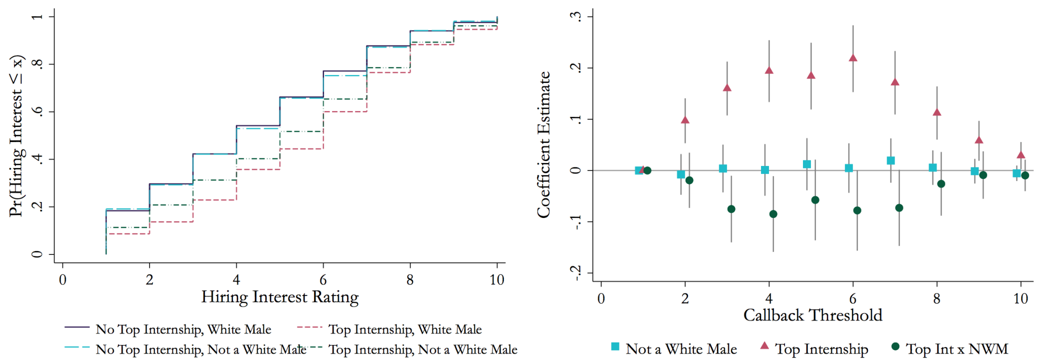
Table B.8—Return to Top Internship by Demographic Group

	Dependent Variable: Hiring Interest				
	OLS	OLS	OLS	GPA-Scaled OLS	Ordered Probit
GPA	2.119	2.184	2.191	1.000	0.889
	(0.145)	(0.150)	(0.129)	(.)	(0.061)
Top Internship	1.147	1.160	1.155	0.527	0.471
	(0.168)	(0.175)	(0.145)	(0.074)	(0.070)
Second Internship	0.468	0.495	0.470	0.214	0.208
	(0.112)	(0.118)	(0.094)	(0.045)	(0.047)
Work for Money	0.109	0.151	0.148	0.067	0.050
	(0.110)	(0.113)	(0.091)	(0.042)	(0.047)
Technical Skills	0.049	0.058	-0.067	-0.031	0.013
	(0.104)	(0.108)	(0.090)	(0.041)	(0.044)
Female, White	0.033	-0.019	0.022	0.010	0.012
	(0.146)	(0.152)	(0.121)	(0.055)	(0.062)
Male, Non-White	-0.060	-0.049	-0.055	-0.025	-0.029
	(0.175)	(0.184)	(0.145)	(0.066)	(0.074)
Female, Non-White	0.081	0.068	0.159	0.073	0.010
	(0.182)	(0.191)	(0.156)	(0.072)	(0.077)
Top Internship × Female, White	-0.464	-0.492	-0.459	-0.209	-0.181
	(0.234)	(0.243)	(0.199)	(0.092)	(0.097)
Top Internship × Male, Non-White	-0.280	-0.316	-0.276	-0.126	-0.116
	(0.279)	(0.288)	(0.233)	(0.107)	(0.116)
Top Internship × Female, Non-White	-0.229	-0.224	-0.316	-0.144	-0.065
	(0.273)	(0.286)	(0.240)	(0.110)	(0.116)
Observations	2880	2880	2880	2880	2880
R^2	0.130	0.182	0.484		
p-value for test of joint significance of Majors	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001
Major FEs	Yes	Yes	Yes	Yes	Yes
Leadership FEs	No	Yes	Yes	Yes	No
Order FEs	No	Yes	Yes	Yes	No
Subject FEs	No	No	Yes	Yes	No

Ordered probit cutpoints: 1.94, 2.31, 2.68, 2.97, 3.29, 3.63, 4.09, 4.55, and 5.06.

Table shows OLS and ordered probit regressions of hiring interest from Equation (1). Robust standard errors are reported in parentheses. *GPA*; *Top Internship*; *Second Internship*; *Work for Money*; *Technical Skills*; *Female, White*; *Male, Non-White*; *Female, Non-White* are characteristics of the hypothetical resume, constructed as described in Section C and in Appendix A.2. Fixed effects for major, leadership experience, resume order, and subject included in some specifications as indicated. R^2 is indicated for each OLS regression. GPA-Scaled OLS presents the results of Column 3 divided by the Column 3 coefficient on GPA, with standard errors calculated by delta method. The p-value of a test of joint significance of major fixed effects is indicated (F-test for OLS, likelihood ratio test for ordered probit).

Figure B.6. : Top Internship × Not a White Male



(a) Empirical CDF

(b) Linear Probability Model

Empirical CDF of *Hiring Interest* (Panel B.6a) and difference in counterfactual callback rates (Panel B.6b) for *Top Internship*, *Not a White Male*, and *Top Internship* × *Not a White Male*. Empirical CDFs show the share of hypothetical candidate resumes with each characteristic with a *Hiring Interest* rating less than or equal to each value. The counterfactual callback plot shows the difference between groups in the share of candidates at or above the threshold—that is, the share of candidates who would be called back in a resume audit study if the callback threshold were set to any given value. 95% confidence intervals are calculated from a linear probability model with an indicator for being at or above a threshold as the dependent variable.

B.5 Relationship Between Likelihood of Acceptance and Human Capital

In evaluating candidates' likelihood of accepting a job offer, the firms in our sample exhibit a potentially surprising belief that candidates with more human capital—indicated by higher GPA, more work experience, and a more prestigious internship—are more likely to accept jobs than candidates with less human capital. This correlation could arise in several ways. First, it is possible that the hiring interest question—which always comes first—creates anchoring for the second question that is unrelated to true beliefs. Second, it is possible that likelihood of acceptance is based on both horizontal fit and vertical quality. Horizontal fit raises both hiring interest and likelihood of acceptance, which would lead to a positive correlation between responses; vertical quality, on the other hand, would be expected to increase hiring interest and decrease likelihood of acceptance, since as it increases hiring interest it also makes workers more desirable for other firms.[44]

If the correlation between *Hiring Interest* and *Likelihood of Acceptance* is driven mostly by horizontal fit, it is important to test whether *Likelihood of Acceptance* is simply a noisy measure of *Hiring Interest*, or whether *Likelihood of Acceptance* contains additional, valuable information. This will help us confirm, for example,

[44]It is also possible that respondents deliberately overstate candidates' likelihood of acceptance in order to be sent the best quality candidates. However, firms who are willing to do this likely have a low cost of interviewing candidates with a lower probability of acceptance. This is in line with the data, where the firms who consistently rate people a 10 on *Likelihood of Acceptance* are among the most prestigious firms in our sample.

that the gender bias we find in *Likelihood of Acceptance* is indeed its own result, rather than a result of bias in *Hiring Interest*. Approaching this is econometrically tricky, since *Hiring Interest* and *Likelihood of Acceptance* are both simultaneous products of the rater's assessment of the randomized resume components. We considered multiple approaches, such as subtracting hiring interest from likelihood of acceptance to capture the difference, regressing likelihood of acceptance on hiring interest and taking residuals, and including controls for hiring interest. All yield similar results, and so we use the latter approach, as it is the most transparent. Despite its econometric issues, we believe this is nonetheless a helpful exercise that can be thought of as akin to a mediation analysis. We want to see if all of the effect on *Likelihood of Acceptance* is mediated through *Hiring Interest*, or if there is independent variation in *Likelihood of Acceptance*.

The first two columns of Table B.9 include a linear control for *Hiring Interest*, while Columns 3 and 4 include fixed effect controls for each level of the *Hiring Interest* rating, examining *Likelihood of Acceptance* within each hiring interest level. We find that after controlling for *Hiring interest*, the relationship between GPA and *Likelihood of Acceptance* becomes negative and statistically significant under all specifications. This indicates that the part of *Likelihood of Acceptance* that is uncorrelated with *Hiring Interest* is indeed negatively correlated with one measure of vertical quality. We also find that the coefficients on *Top Internship* and *Second Internship* become statistically indistinguishable from zero.

Under all specifications, the coefficients on *Female, White* and *Female, Non-White* remain negative and significant, indicating that employers believe women are less likely to accept jobs if offered, even controlling for the firm's interest in the candidate.

Thus, we conclude that *Likelihood of Acceptance* does provide additional information above and beyond *Hiring Interest*. We hope future research will tackle the question of how to measure beliefs about *Likelihood of Acceptance* even more accurately, how to disentangle them from *Hiring Interest*, and exactly what role they play in hiring decisions.

Table B.9—Likelihood of Acceptance with Hiring Interest Controls

	Dependent Variable: Likelihood of Acceptance			
	OLS	Ordered Probit	OLS	Ordered Probit
GPA	-0.812	-0.638	-0.823	-0.660
	(0.082)	(0.064)	(0.081)	(0.065)
Top Internship	0.033	0.000	0.031	0.001
	(0.053)	(0.041)	(0.053)	(0.041)
Second Internship	0.066	0.051	0.068	0.049
	(0.063)	(0.048)	(0.063)	(0.048)
Work for Money	0.095	0.082	0.095	0.087
	(0.061)	(0.047)	(0.061)	(0.048)
Technical Skills	-0.053	-0.057	-0.061	-0.066
	(0.060)	(0.045)	(0.059)	(0.045)
Female, White	-0.145	-0.078	-0.147	-0.082
	(0.064)	(0.048)	(0.064)	(0.049)
Male, Non-White	0.002	-0.016	0.001	-0.008
	(0.074)	(0.058)	(0.074)	(0.058)
Female, Non-White	-0.182	-0.154	-0.185	-0.159
	(0.074)	(0.059)	(0.074)	(0.059)
Hiring Interest	0.704	0.478	FEs	FEs
	(0.014)	(0.010)		
Observations	2880	2880	2880	2880
R^2	0.766		0.768	
p-value for test of joint significance of Majors	0.025	< 0.001	0.031	< 0.001
Major FEs	Yes	Yes	Yes	Yes
Leadership FEs	Yes	No	Yes	No
Order FEs	Yes	No	Yes	No
Subject FEs	Yes	No	Yes	No

Cutpoints (Col 2): -1.82, -1.18, -0.55, -0.11, 0.49, 1.07, 1.71, 2.39, 2.81.

Cutpoints (Col 4): -2.00, -1.26, -0.58, -0.14, 0.45, 1.01, 1.62, 2.28, 2.69.

Table shows OLS and ordered probit regressions of *Likelihood of Acceptance* from Equation (1), with additional controls for *Hiring Interest*. Robust standard errors are reported in parentheses. *GPA*; *Top Internship*; *Second Internship*; *Work for Money*; *Technical Skills*; *Female, White*; *Male, Non-White*; *Female, Non-White* and major are characteristics of the hypothetical resume, constructed as described in Section C and in Appendix A.2. Fixed effects for major, leadership experience, resume order, and subject included in some specifications as indicated. R^2 is indicated for each OLS regression. The p-values of tests of joint significance of major fixed effects and demographic variables are indicated (F-test for OLS, likelihood ratio test for ordered probit).

C Pitt Appendix

In our replication study at the University of Pittsburgh, we followed a similar approach to that described for our experimental waves at Penn in Section A.2. The tool structure was essentially the same as at Penn, with references to Penn replaced with Pitt in the instructions, and the reference to Wharton removed from the major selection page. Resume structure was identical to that described in Sections A.2.1 and A.2.2. Names were randomized in the same manner as described in Section A.2.3. The education section of each resume at Pitt followed the same structure as that described in Section A.2.4, but had a degree from the University of Pittsburgh, with majors, schools, and degrees randomly drawn from a set of Pitt's offerings. In selecting majors for our Pitt replication, we attempted to match the Penn major distribution as closely as possible, but some majors were not offered at both schools. When necessary, we selected a similar major instead. The majors, schools, classifications, and probabilities for Pitt are shown in Table C.1.

We used a single pool of Pitt resumes for both the hypothetical resume elements and for a candidate pool for Pitt employers, saving significant effort on scraping and parsing. These components were compiled and randomized in much the same way as at Penn, as described in Section A.2.5. For *Top Internship* at Pitt, we collected work experiences from Pitt resumes at one of Pitt's most frequent employers, or at one of the employers used to define *Top Internship* at Penn. Similarly, Pitt *Work for Money* was identified from the same list of identifying phrases shown in Table A.5. *Technical Skills* were randomized in the same way as at Penn, described in A.2.5.

Table C.1—Majors in Generated Pitt Resumes

Type	**School**	**Major**	**Probability**
Humanities & Social Sciences	Dietrich School of Arts and Sciences	BS in Economics	0.4
		BA in Economics	0.2
		BS in Political Science	0.075
		BS in Psychology	0.075
		BA in Communication Science	0.05
		BA in English Literature	0.05
		BA in History	0.05
		BA in History of Art and Architecture	0.025
		BA in Philosophy	0.025
		BA in Social Sciences	0.025
		BA in Sociology	0.025
STEM	Dietrich School of Arts and Sciences	BS in Natural Sciences	0.1
		BS in Molecular Biology	0.075
		BS in Bioinformatics	0.05
		BS in Biological Sciences	0.05
		BS in Chemistry	0.05
		BS in Mathematical Biology	0.05
		BS in Mathematics	0.05
		BS in Physics	0.05
		BS in Statistics	0.025
	Swanson School of Engineering	BS in Computer Engineering	0.15
		BS in Mechanical Engineering	0.075
		BS in Bioengineering	0.05
		BS in Chemical Engineering	0.05
		BS in Computer Science	0.05
		BS in Electrical Engineering	0.05
		BS in Materials Science and Engineering	0.05
		BS in Civil Engineering	0.025

Majors, degrees, schools within Pitt, and their selection probability by major type. Majors (and their associated degrees and schools) were drawn with replacement and randomized to resumes after subjects selected to view either Humanities & Social Sciences resumes or STEM resumes.

Table C.2—Effects by Major Type at Pitt

	Dependent Variable: Hiring Interest									
	Humanities & Social Sciences					STEM				
	OLS	OLS	OLS	GPA-Scaled OLS	Ordered Probit	OLS	OLS	OLS	GPA-Scaled OLS	Ordered Probit
GPA	0.249	0.294	0.249	1.000	0.097	0.518	0.445	0.340	1.000	0.167
	(0.189)	(0.203)	(0.150)	(.)	(0.073)	(0.245)	(0.274)	(0.187)	(.)	(0.092)
Top Internship	0.267	0.290	0.298	1.196	0.098	0.164	0.193	0.174	0.513	0.058
	(0.139)	(0.150)	(0.108)	(0.834)	(0.053)	(0.156)	(0.174)	(0.110)	(0.419)	(0.060)
Second Internship	0.438	0.496	0.446	1.791	0.169	-0.022	-0.076	-0.082	-0.243	-0.002
	(0.146)	(0.154)	(0.112)	(1.163)	(0.057)	(0.184)	(0.204)	(0.133)	(0.414)	(0.072)
Work for Money	0.323	0.354	0.355	1.425	0.121	-0.063	-0.039	-0.037	-0.109	-0.001
	(0.145)	(0.155)	(0.109)	(0.958)	(0.057)	(0.186)	(0.207)	(0.129)	(0.386)	(0.072)
Technical Skills	-0.014	-0.036	0.037	0.149	-0.004	0.376	0.459	0.283	0.834	0.153
	(0.131)	(0.143)	(0.103)	(0.418)	(0.051)	(0.179)	(0.199)	(0.129)	(0.611)	(0.067)
Female, White	-0.080	-0.177	-0.043	-0.174	-0.021	-0.043	0.033	0.049	0.145	-0.013
	(0.149)	(0.160)	(0.113)	(0.467)	(0.058)	(0.184)	(0.203)	(0.133)	(0.395)	(0.072)
Male, Non-White	0.089	0.037	-0.155	-0.621	0.044	-0.045	0.028	0.083	0.246	-0.041
	(0.175)	(0.189)	(0.130)	(0.634)	(0.068)	(0.232)	(0.259)	(0.160)	(0.481)	(0.089)
Female, Non-White	-0.196	-0.331	-0.073	-0.294	-0.072	-0.160	-0.055	0.091	0.267	-0.036
	(0.180)	(0.193)	(0.140)	(0.592)	(0.069)	(0.225)	(0.258)	(0.160)	(0.482)	(0.089)
Observations	2000	2000	2000	2000	2000	1440	1440	1440	1440	1440
R^2	0.015	0.078	0.553			0.031	0.109	0.651		
p-value for test of joint significance of Majors	0.713	0.787	0.185	0.185	0.821	0.015	0.023	< 0.001	< 0.001	0.014
Major FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Leadership FEs	No	Yes	Yes	Yes	No	No	Yes	Yes	Yes	No
Order FEs	No	Yes	Yes	Yes	No	No	Yes	Yes	Yes	No
Subject FEs	No	No	Yes	Yes	No	No	No	Yes	Yes	No

Ordered probit cutpoints (Column 5): -0.38, -0.13, 0.19, 0.42, 0.68, 0.98, 1.40, 1.88, 2.45.

Ordered probit cutpoints (Column 10): 0.40, 0.61, 0.85, 1.02, 1.16, 1.31, 1.58, 1.95, 2.22.

Table shows OLS and ordered probit regressions of *Hiring Interest* from Equation (1). Robust standard errors are reported in parentheses. *GPA*; *Top Internship*; *Second Internship*; *Work for Money*; *Technical Skills*; *Female, White*; *Male, Non-White*; *Female, Non-White* and major are characteristics of the hypothetical resume, constructed as described in Section C and in Appendix A.2. Fixed effects for major, leadership experience, resume order, and subject included as indicated. R^2 is indicated for each OLS regression. The p-values of tests of joint significance of major fixed effects and demographic variables are indicated (F-test for OLS, likelihood ratio test for ordered probit) after a Bonferroni correction for analyzing two subgroups.

Table C.3—Likelihood of Acceptance at Pitt

	Dependent Variable: Likelihood of Acceptance			
	OLS	OLS	OLS	Ordered Probit
GPA	0.178	0.161	0.010	0.071
	(0.148)	(0.155)	(0.101)	(0.057)
Top Internship	0.233	0.245	0.235	0.087
	(0.103)	(0.108)	(0.068)	(0.040)
Second Internship	0.224	0.221	0.199	0.074
	(0.114)	(0.119)	(0.077)	(0.045)
Work for Money	0.142	0.143	0.130	0.050
	(0.114)	(0.120)	(0.074)	(0.044)
Technical Skills	0.195	0.187	0.111	0.084
	(0.106)	(0.110)	(0.070)	(0.040)
Female, White	-0.063	-0.079	0.015	-0.027
	(0.115)	(0.122)	(0.077)	(0.045)
Male, Non-White	-0.000	-0.012	-0.064	-0.011
	(0.139)	(0.145)	(0.091)	(0.054)
Female, Non-White	-0.198	-0.197	-0.048	-0.070
	(0.140)	(0.147)	(0.090)	(0.055)
Observations	3440	3440	3440	3440
R^2	0.037	0.061	0.643	
p-value for test of joint significance of Majors	< 0.001	< 0.001	< 0.001	< 0.001
Major FEs	Yes	Yes	Yes	Yes
Leadership FEs	No	Yes	Yes	No
Order FEs	No	Yes	Yes	No
Subject FEs	No	No	Yes	No

Ordered probit cutpoints: -0.10, 0.14, 0.38, 0.58, 0.86, 1.08, 1.42, 1.86, and 2.35.

Table shows OLS and ordered probit regressions of *Likelihood of Acceptance* from Equation (1). Robust standard errors are reported in parentheses. *GPA*; *Top Internship*; *Second Internship*; *Work for Money*; *Technical Skills*; *Female, White*; *Male, Non-White*; *Female, Non-White* and major are characteristics of the hypothetical resume, constructed as described in Section C and in Appendix A.2. Fixed effects for major, leadership experience, resume order, and subject included in some specifications as indicated. R^2 is indicated for each OLS regression. The p-values of tests of joint significance of major fixed effects and demographic variables are indicated (F-test for OLS, likelihood ratio test for ordered probit).

Table C.4—Likelihood of Acceptance by Major Type at Pitt

	Dependent Variable: Likelihood of Acceptance							
	Humanities & Social Sciences				STEM			
	OLS	OLS	OLS	Ordered Probit	OLS	OLS	OLS	Ordered Probit
GPA	-0.064	-0.044	-0.173	-0.007	0.499	0.427	0.278	0.155
	(0.187)	(0.202)	(0.127)	(0.074)	(0.241)	(0.268)	(0.181)	(0.091)
Top Internship	0.261	0.248	0.263	0.097	0.210	0.227	0.214	0.078
	(0.137)	(0.149)	(0.091)	(0.053)	(0.155)	(0.173)	(0.112)	(0.060)
Second Internship	0.353	0.435	0.373	0.124	0.043	-0.026	-0.020	0.020
	(0.146)	(0.156)	(0.095)	(0.057)	(0.183)	(0.201)	(0.131)	(0.071)
Work for Money	0.271	0.294	0.303	0.100	-0.051	-0.045	-0.034	-0.009
	(0.144)	(0.155)	(0.095)	(0.057)	(0.184)	(0.205)	(0.126)	(0.071)
Technical Skills	-0.013	0.004	-0.008	-0.005	0.521	0.638	0.382	0.214
	(0.130)	(0.140)	(0.086)	(0.051)	(0.178)	(0.195)	(0.128)	(0.066)
Female, White	-0.064	-0.149	-0.001	-0.035	-0.081	-0.007	-0.025	-0.014
	(0.148)	(0.159)	(0.097)	(0.058)	(0.183)	(0.204)	(0.136)	(0.071)
Male, Non-White	0.110	0.060	-0.132	0.033	-0.152	-0.080	0.022	-0.072
	(0.173)	(0.185)	(0.112)	(0.068)	(0.232)	(0.259)	(0.162)	(0.089)
Female, Non-White	-0.138	-0.258	-0.095	-0.062	-0.286	-0.218	-0.031	-0.068
	(0.180)	(0.194)	(0.118)	(0.069)	(0.224)	(0.258)	(0.158)	(0.088)
Observations	2000	2000	2000	2000	1440	1440	1440	1440
R^2	0.010	0.069	0.666		0.036	0.110	0.654	
p-value for test of joint significance of Majors	1.436	1.550	1.061	1.701	0.006	0.016	< 0.001	0.008
Major FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Leadership FEs	No	Yes	Yes	No	No	Yes	Yes	No
Order FEs	No	Yes	Yes	No	No	Yes	Yes	No
Subject FEs	No	No	Yes	No	No	No	Yes	No

Ordered probit cutpoints (Column 4): -0.59, -0.34, -0.11, 0.14, 0.47, 0.76, 1.12, 1.59, 2.37.

Ordered probit cutpoints (Column 8): 0.31, 0.56, 0.78, 0.93, 1.12, 1.25, 1.56, 1.96, 2.26.

Table shows OLS and ordered probit regressions of *Likelihood of Acceptance* from Equation (1). *GPA*; *Top Internship*; *Second Internship*; *Work for Money*; *Technical Skills*; *Female, White*; *Male, Non-White*; *Female, Non-White* and major are characteristics of the hypothetical resume, constructed as described in Section C and in Appendix A.2. Fixed effects for major, leadership experience, resume order, and subject included as indicated. R^2 is indicated for each OLS regression. The p-values of tests of joint significance of major fixed effects and demographic variables are indicated (F-test for OLS, likelihood ratio test for ordered probit) after a Bonferroni correction for analyzing two subgroups.

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