The Value of Postsecondary Credentials in the Labor Market: An Experimental Study

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Online Appendix

Appendix Table 1: Awards and Job Vacancy Shares by Labor Market

Combined Statistical Area (CSA)	Health Certificates	Business		Share of All FT Vacancies
		AA	BA	
	(1)	(2)	(3)	(4)
New York-Newark, NY-NJ-CT-PA	0.059	0.088	0.064	0.041
Los Angeles-Long Beach, CA	0.082	0.040	0.043	0.032
Chicago-Naperville, IL-IN-WI	0.041	0.043	0.031	0.041
Miami-Fort Lauderdale-Port St. Lucie, FL	0.033	0.010	0.019	0.019
San Jose-San Francisco-Oakland, CA	0.018	0.021	0.017	0.029
Total share of U.S. awards in category	0.233	0.202	0.174	0.163

Notes: Occupation categories are based on the Classification of Instructional Programs (CIP) codes. Certificates include awards of less than one year and awards of more than one but fewer than two years. The share of full-time job vacancies is computed by summing the number of vacancies posted in the last 24 hours over three consecutive days, and then dividing the share of jobs in each occupation or keyword search into the total. FT stands for full-time.

Appendix Table 2: Institutions in the Resume Audit Study

Name	Sector	City
University of Phoenix	For-Profit (Online)	New York, Chicago, SF, LA, Miami
Colorado Technical University	For-Profit (Online)	New York, Chicago, SF, LA, Miami
American Public University	For-Profit (Online)	New York, Chicago, SF, LA, Miami
Ashford University	For-Profit (Online)	New York, Chicago, SF, LA, Miami
Kaplan University	For-Profit (Online)	New York, Chicago, SF, LA, Miami
Strayer University	For-Profit (Online)	New York, Chicago, SF, LA, Miami
DeVry University	For-Profit (Online)	New York, Chicago, SF, LA, Miami
Everest College/Institute	For-Profit (Local Not Online)	New York, Chicago, SF, LA, Miami
Sanford-Brown Institute	For-Profit (Local Not Online)	New York, Miami
Monroe College	For-Profit (Local Not Online)	New York
Lincoln Technical Institute	For-Profit (Local Not Online)	New York
Coyne College	For-Profit (Local Not Online)	Chicago
Midwestern Career College	For-Profit (Local Not Online)	Chicago
Northwestern College	For-Profit (Local Not Online)	Chicago
J Renee Career Facilitation	For-Profit (Local Not Online)	Chicago
Brown Mackie College	For-Profit (Local Not Online)	Chicago
Florida National University	For-Profit (Local Not Online)	Miami
Southeastern College	For-Profit (Local Not Online)	Miami
Fortis Institute	For-Profit (Local Not Online)	Miami
Florida Career College	For-Profit (Local Not Online)	Miami
Dade Medical College	For-Profit (Local Not Online)	Miami
Heald College	For-Profit (Local Not Online)	SF, LA
Unitek College	For-Profit (Local Not Online)	SF
Carrington College	For-Profit (Local Not Online)	SF
NCP College of Nursing	For-Profit (Local Not Online)	SF
Gurnick Academy of Medical Arts	For-Profit (Local Not Online)	SF
Summit College	For-Profit (Local Not Online)	LA
UEI College	For-Profit (Local Not Online)	LA
American Career College	For-Profit (Local Not Online)	LA
Concorde Career College	For-Profit (Local Not Online)	LA
North-West College	For-Profit (Local Not Online)	LA
CUNY – Medgar Evers College	Public	New York
Hostos Community College	Public	New York
Bronx Community College	Public	New York
LaGuardia Community College	Public	New York
Manhattan Community College	Public	New York
Queensborough Community College	Public	New York
Kingsborough Community College	Public	New York
Baruch College	Public (Not Selective)	New York
Brooklyn College	Public (Not Selective)	New York
Lehman College	Public (Not Selective)	New York
College of Staten Island	Public (Not Selective)	New York
Hunter College	Public (Not Selective)	New York
Queens College	Public (Not Selective)	New York
Stony Brook University	Public (Selective)	New York
Joliet Junior College	Public	Chicago
Richard Daley College	Public	Chicago

Harry Truman College	Public	Chicago
Wilbur Wright College	Public	Chicago
College of DuPage	Public	Chicago
Triton College	Public	Chicago
Olive Harvey College	Public	Chicago
Moraine Valley Community College	Public	Chicago
Elgin Community College	Public	Chicago
Chicago State University	Public (Not Selective)	Chicago
Northeastern Illinois University	Public (Not Selective)	Chicago
University of Illinois, Chicago	Public (Selective)	Chicago
Univ. of IL, Urbana / Champaign	Public (Selective)	Chicago
Palm Beach State College	Public	Miami
Broward College	Public	Miami
Miami Dade College	Public	Miami
Florida International University	Public (Not Selective)	Miami
University of Florida	Public (Selective)	Miami
De Anza College	Public	San Francisco
City College of San Francisco	Public	San Francisco
Skyline College	Public	San Francisco
San Joaquin Delta College	Public	San Francisco
San Jose City College	Public	San Francisco
Contra Costa College	Public	San Francisco
California State Univ., East Bay	Public (Not Selective)	San Francisco
Sonoma State University	Public (Not Selective)	San Francisco
University of California, Berkeley	Public (Selective)	San Francisco, Los Angeles
Chaffey College	Public	Los Angeles
Long Beach City College	Public	Los Angeles
Riverside City College	Public	Los Angeles
Pasadena City College	Public	Los Angeles
Santa Ana College	Public	Los Angeles
College of the Canyons	Public	Los Angeles
Glendale Community College	Public	Los Angeles
Santa Monica College	Public	Los Angeles
East Los Angeles College	Public	Los Angeles
El Camino Community College	Public	Los Angeles
Cerritos College	Public	Los Angeles
California State Univ., Fullerton	Public (Not Selective)	Los Angeles
California State Univ., Northridge	Public (Not Selective)	Los Angeles
California State Univ., Long Beach	Public (Not Selective)	Los Angeles
California State Univ., Los Angeles	Public (Not Selective)	Los Angeles
Univ. of California, Los Angeles	Public (Selective)	San Francisco, Los Angeles

Appendix Table 3: Core Results from Interview Callback Regressions

	(1) Interview	(2) Interview	(3) Interview	(4) Interview	(5) Interview
For-Profit (AA)	-0.0030	-0.0067			
	(0.0042)	(0.0093)			
× Salary (in $10,000s)		0.0007			
		(0.0016)			
For-Profit (BA)	-0.0001	-0.0021			
	(0.0059)	(0.0138)			
× Salary (in $10,000s)		0.0009			
		(0.0026)			
Public (AA)	-0.0004	-0.0091			
	(0.0039)	(0.0083)			
× Salary (in $10,000s)		0.0020			
		(0.0017)			
For-Profit BA, Online			-0.0127***	-0.0249**	
			(0.0041)	(0.0115)	
× Salary (in $10,000s)				0.0022	
				(0.0016)	
For-Profit BA, Local			-0.0054	-0.0073	
			(0.0090)	(0.0215)	
× Salary (in $10,000s)				0.0007	
				(0.0027)	
Selective Public BA			-0.0018	-0.0402**	
			(0.0067)	(0.0160)	
× Salary (in $10,000s)				0.0070***	
				(0.0026)	
FP certificate, no degree required					-0.0036
					(0.0094)
Public certificate, no degree required					0.0102
					(0.0071)
FP certificate, degree required					0.0026
					(0.0058)
Baseline interview callback rate	0.060	0.060	0.043	0.043	0.034
Occupation / Degree required	Business, no degree	Business, no degree	Business, BA	Business, BA	Health
Number of observations	4,004	3,753	4,100	3,914	2,388
Vacancy fixed effects	X	X	X	X	X

Notes: The dependent variable is an indicator variable for an interview callback, defined as a callback (by phone or email) from the potential employer that includes mention of an interview. The omitted education category is no postsecondary degree in cols. (1) and (2), a non-selective public BA in cols. (3) and (4), and no postsecondary degree or certificate in col. (5). All the specifications include fixed effects for skill template, work history template, and name (applicant initials). The line "× Salary" is an interaction of the variable above that line times the expected salary for the job opening (based on the median salary for the job title). Standard errors are clustered at the vacancy level.
*** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$

Appendix Table 4: Pooled Analysis of For-Profit On-line vs. Local Institutions (for Business Jobs including vacancies both with a BA required and with no BA degree required)

	(1) Callback	(2) Callback
For-Profit AA/BA, Online	-0.0142***	-0.0151***
	[0.0048]	[0.0044]
For-Profit AA/BA, Local	0.0044	0.0012
	[0.0109]	[0.0080]
High School Degree Only	-0.0026	-0.0071
	[0.0090]	[0.0062]
Vacancy Fixed Effects		X
Observations	8,104	8,104
F(FP AA/BA, Online= FP AA/BA, Local)	0.118	0.055
F(FP AA/BA, Online = HS Only)	0.180	0.202
F(FP AA/BA, Local = HS Only)	0.576	0.376

Notes: The dependent variable is an indicator variable for any personalized callback from the potential employer. Standard errors are clustered at the vacancy level. The omitted education category is a degree (BA or AA) from a public institution. All the specifications include fixed effects for skill template, work history template, and name (applicant initials). Col. (1) includes indicators for race/gender and labor market. The sample used in the regressions pools the sample of business jobs that do not require a bachelor's degree from Table 4 with the sample of business jobs that require a bachelor's degree from Table 5.

*** $p < 0.01$

Appendix Table 5: Heterogeneous Callback Returns by Race of Applicant

	No Degree Required	Degree Required
	(1)	(2)
	Callback	Callback
For-profit, white applicant	0.0150**	-0.0170**
	(0.0074)	(0.0070)
Public, white applicant	0.0233**	
	(0.0088)	
For-profit, nonwhite applicant	-0.0183**	-0.0149**
	(0.0083)	(0.0057)
Public, nonwhite applicant	-0.0073	
	(0.0081)	
Vacancy Fixed Effects	X	X
Number of observations	4,952	5,540
F(FP white=FP nonwhite)	0.003	0.813
F(Public white=Public nonwhite)	0.010	

Notes: The dependent variable is an indicator variable for any personalized callback from the potential employer. Standard errors are clustered at the vacancy level. The regressions in both columns include fixed effects for skill template, work history template, and name (i.e. applicant initials). The sample used in col. (1) pools business with no degree required and health jobs with no certificate required. The sample used in col. (2) pools business jobs with a BA required and health jobs with a certificate required. No postsecondary degree or certificate is the omitted education group in col. (1), and a degree or certificate from a public institution is the omitted education group in col. (2).

** $p < 0.05$
* $p < 0.10$

Appendix Table 6: Heterogeneous Callback Returns by Gender of Applicant

	Business, No Degree Required		Business, BA Required		Health, No Certificate Required	Health, Certificate Required
	(1)		(2)		(3)	(4)
	Callback		Callback		Callback	Callback
FP AA, male	-0.004	FP local, male	-0.021	FP, male	-0.010	0.006
	(0.008)		(0.018)		(0.022)	(0.012)
FP AA, female	0.000	FP local, female	0.008	FP, female	-0.020	-0.017
	(0.011)		(0.016)		(0.015)	(0.014)
FP, BA male	0.012	FP online, male	-0.023***	Public, male	0.050**	
	(0.010)		(0.008)		(0.021)	
FP, BA female	0.005	FP online, female	-0.019**	Public, female	0.024	
	(0.013)		(0.008)		(0.020)	
Public AA, male	0.001	Public selective, male	0.002			
	(0.010)		(0.013)			
Public AA , female	0.004	Public selective, female	-0.001			
	(0.009)		(0.014)			
Number of observations	4,004	Number of observations	4,100	Number of observations	948	1,440
R-squared	0.011	R-squared	0.018	R-squared	0.072	0.037

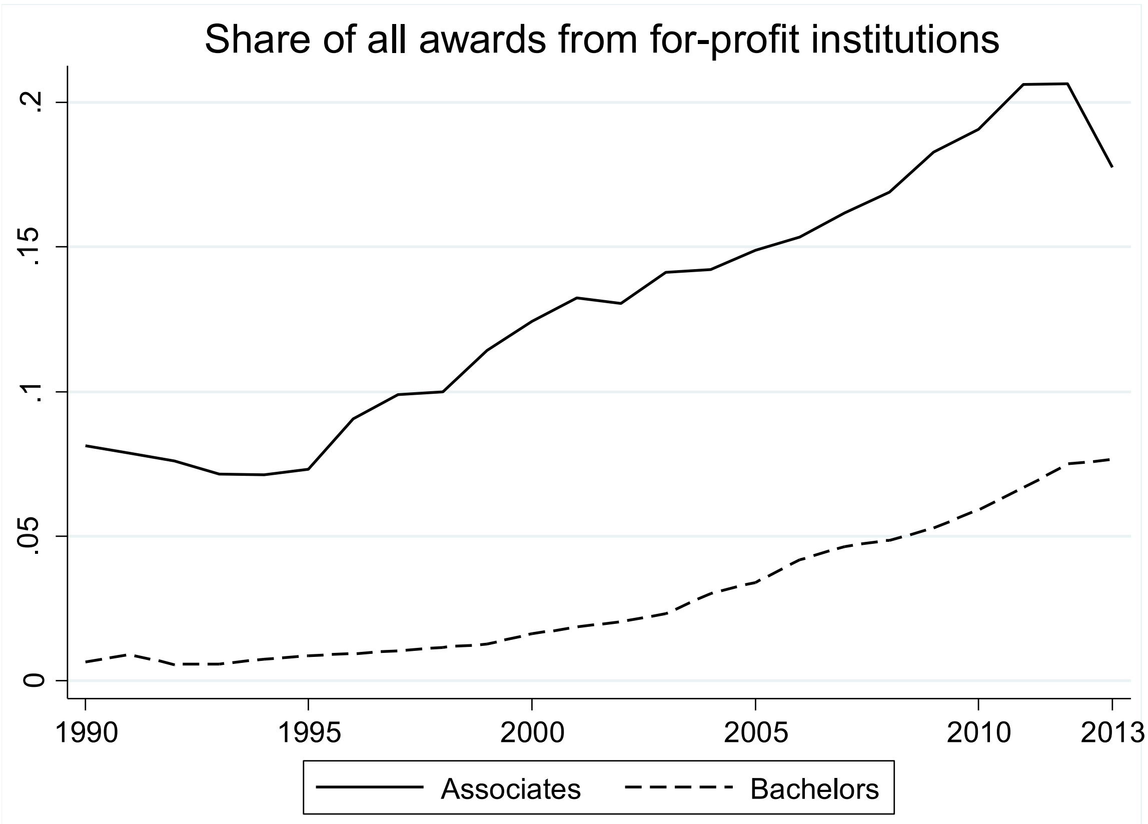
Notes: The dependent variable is an indicator variable for any personalized callback from the potential employer. Standard errors are clustered at the vacancy level. The regressions include fixed effects for vacancy, skill template, work history template, and name (applicant initials). The base education category is no postsecondary degree or certificate in cols. (1) and (3), a non-selective public BA in col. (2), and a public certificate in col. (4). All the educational credentials in col. (2) are BAs, and all the credentials in cols. (3) and (4) are certificates.
*** $p < 0.01$, ** $p < 0.05$,* $p < 0.10$

Appendix Table 7: Heterogeneous Callback Returns by Occupation

	Business, no degree Required		Business, BA Required		Licensed Practical Nurse	Pharmacy Technician	Medical Assistant, Certificate Required	Medical Assistant, No Certificate Required
	(1)		(2)		(3)	(4)	(5)	(6)
	Callback		Callback		Callback	Callback	Callback	Callback
FP AA, sales	-0.002	FP BA local, sales	-0.012	For profit cert	-0.012	0.055	-0.011	-0.015
	(0.008)		(0.022)		(0.011)	(0.040)	(0.013)	(0.013)
FP AA, accounting	-0.001	FP BA local, accounting	-0.002	Public cert				0.036**
	(0.009)		(0.012)					(0.015)
FP BA, sales	0.008	FP BA online, sales	-0.029***					
	(0.010)		(0.010)					
FP BA, accounting	0.011	FP BA online, accounting	-0.012**					
	(0.014)		(0.006)					
Public AA, sales	0.005	Public BA selective, sales	-0.012					
	(0.008)		(0.014)					
Public AA, accounting	-0.005	Public BA selective, accounting	0.016					
	(0.010)		(0.013)					
Number of observations	4,004	Number of observations	4,100	Number of observations	804	200	436	948
R-squared	0.011	R-squared	0.018	R-squared	0.016	0.213	0.041	0.071

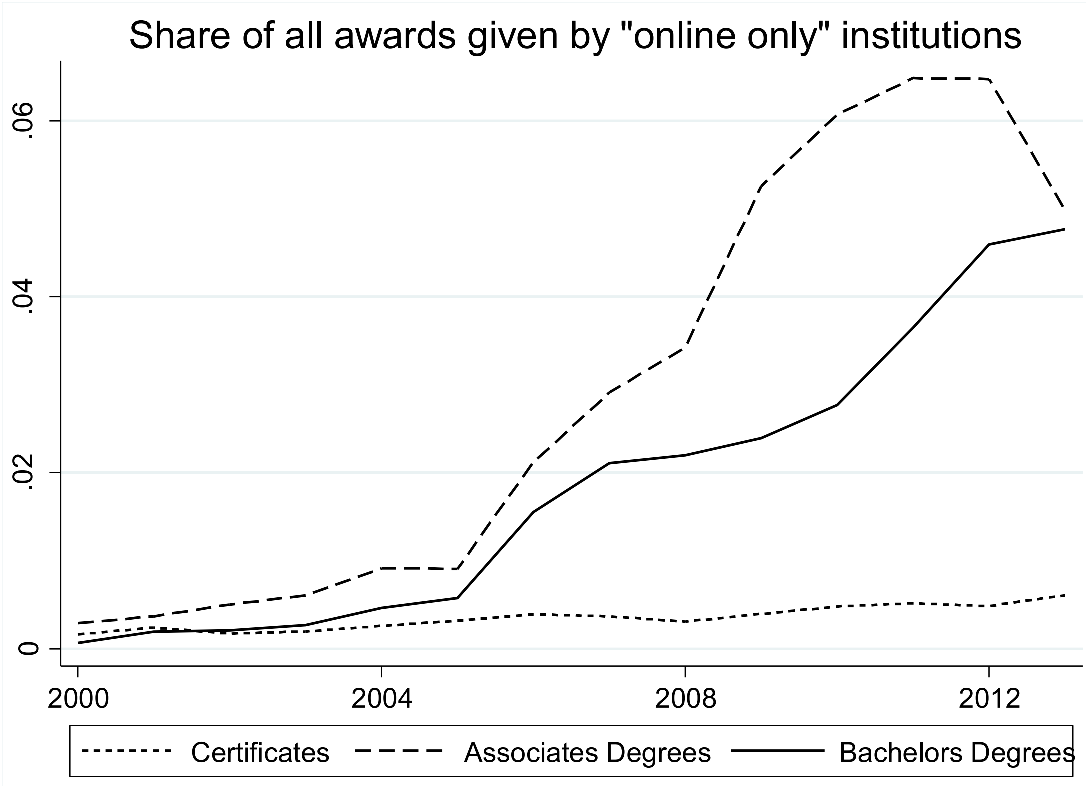
Notes: The dependent variable is an indicator variable for any personalized callback from the potential employer. Standard errors are clustered at the vacancy level. The regressions include fixed effects for vacancy, skill template, work history template, and name (applicant initials). The base education category is no postsecondary degree or certificate in cols. (1) and (6), a non-selective public BA in col. (2), and a public certificate in cols. (3), (4), and (5).
*** $p < 0.01$, ** $p < 0.05$,* $p < 0.10$

Appendix Figure 1: For-Profit Institution Share of Degrees Awarded by Title IV Postsecondary Institutions, 1990-2013



Source: Integrated Postsecondary Education Data System (IPEDS).

Appendix Figure 2: Share of Postsecondary Awards from “Online Only” Institutions, 2000-2013



Source: Integrated Postsecondary Education Data System (IPEDS). IPEDS collects data on enrollment and completions at the campus (not institution) level, and “Online Only” institutions are defined as campuses that are solely dedicated to distance education or that have “online” in the institution title. See the text for details.

Appendix A: Details of Resume Construction and Job Application Procedure

We adopt a standard template for all resumes that lists (in order) name, contact information, degree, work history, and skills and additional information. Job seekers who post their resumes in the resume bank (from which we extracted work history information) are required to submit information in a series of fields. A resume is then produced using a standardized template. We follow the template exactly, except that we list degree directly beneath contact information to maximize salience (the default is to list the degree after work experience, which is more common among experienced job seekers). Most resumes have a "skills" section, which often includes knowledge of common software programs (i.e., Microsoft Office), standard certifications (i.e., CPR certification for health jobs), and sometimes claims of "soft" skills like "team player" and "detail-oriented." Similar to our method of assigning work experience, we select entire skills templates from actual graduates at each type of institution and randomly assign them across resumes. In cases where skills are extremely common (i.e., Microsoft Office), we assign them to all resumes.

We include a specific high school and graduation date on every resume. Listing the date of high school graduation bounds past work history and ensures that resumes are not hiding work history gaps, known to be important to employers (Kroft, Lange, and Notowidigdo 2013). It is not unusual for resumes with a postsecondary degree to list the name of the applicant's high school. Moreover, it is common for resumes that do not have a postsecondary credential to list a high school diploma and the school attended, perhaps because many jobs require applicants to have a high school diploma or GED. Using the Common Core of Data (CCD), we sort all regular (non-charter, non-specialized) high schools in a CSA by racial composition and select the four schools that represent the median student of each race. We randomly assign each of these high schools to resumes within a racial category.

Each resume lists an email address and a local phone number that we created to monitor callbacks. We use a standard voicemail recording that prompts callers to leave a message, and we record all callbacks and emails that were directed to the applicant (i.e., not mass emails to job candidates) as data. Following our IRB-required protocol, we destroyed the phone and email records immediately after collecting the relevant information for our study, and callbacks and email contacts were not answered. Finally, we generated four fictitious addresses in large apartment complexes within each labor market and randomly assigned them to resumes on the relatively rare occasions when an address was requested.

Members of our research team were assigned to particular labor markets and degree programs and instructed to search daily for eligible jobs in each category using a combination of keyword searches and default occupational classifications used by the website that are based on the Occupational Information Network classification scheme (O*NET).

In addition to the job requirements described in the previous section, we attempted to eliminate job postings from staffing companies and those that gave commission-based pay. Our concern with staffing companies was that their postings were meant to add applicants to a resume pool, rather than actual job vacancies. Commission-based jobs did not appear to provide stable employment opportunities for graduates of postsecondary programs (e.g., "20 free sales leads!"). We managed to eliminate most, but probably not all, staffing companies and commission-based pay jobs.

After identifying a set of vacancies that satisfied the requirements of our study, members of our research team generated resumes with randomly assigned combinations of characteristics using the *Resume Randomizer* program developed by Lahey and Beasley (2009). The four generated resumes were then uploaded to each job vacancy in random order and using different accounts for each resume. After completing each application, key information about the job was saved including firm name, job title, requirements, salary if available, and the text of the job description. Recording vacancy information helped us ensure that we did not apply to the same job if it was re-posted, and that we did not apply to the same firm within a four-week period.

Appendix B: Measuring job quality by collecting job title-specific salaries

To estimate expected salaries for the job titles to which we apply, we collect data from indeed.com, a website with a database of millions of job postings that provides median salaries by job title based on postings from the last 12 months.

The indeed.com website allows one to search for the typical (median) salaries associated with specific job titles (job title search) or salaries associated with job postings containing particular keywords (keyword search). The site also allows one to search for salaries associated with job postings in a particular location, or to search for salaries nationally.

We use a data-scraping program (available from the authors upon request) to enter into the indeed.com salary search bar (http://www.indeed.com/salary) the job titles from the postings to which we applied, one title at a time.

We tried to ensure that our results are robust to measurement error arising from imperfect matches of the job titles to which we applied with job postings in the indeed.com database.[1] In particular, we checked the sensitivity of our findings to conducting each job title search in four different ways:

1. National title search: we did not specify the location of the job, and we matched the title of the job to which we applied only to job posting titles in the indeed.com database.
2. National keyword search: we did not specify the location of the job, and we matched the title of the job to which we applied to job posting titles or to other keywords in the indeed.com database.
3. Labor market-specific title search: we specified the location of the job to which we applied, and we matched the title of the job to which we applied only to job posting titles in the indeed.com database.
4. Labor market-specific keyword search: we specified the location of the job to which we applied, and we matched the title of the job to which we applied to job posting titles or to other keywords in the indeed.com database.

The results are not much affected by the particular choice of indeed.com queries for job salaries. Our baseline query is the national title search. This approach limits Type I errors arising from irrelevant (for our purposes) information in job postings and limits Type II errors by allowing for close matches between the job titles to which we applied in our resume audit study and job posting titles in the indeed.com database from across the country.

[1] We were concerned about both Type I and Type II errors. A Type I error (indeed.com matches a job title to which we applied with a job posting in their database, when in fact the jobs were very different) would be of greatest concern in broader searches (national, keyword searches). For example, a search for "Sales Associate" may yield a match with an "Administrative Assistant" job posting on indeed.com, if the "Administrative Assistant" job posting included in the job description mention that the position would be in support of a sales team. A Type II error (indeed.com fails to match a job title to which we applied to similar job postings in their database) would be of greatest concern in narrower searches (labor market-specific, title searches).

Despite the steps we took to standardize salaries across similar job titles, significant variation remained. In particular, salaries for sales and customer service jobs varied considerably for seemingly arbitrary differences in job titles. For example, a "sales representative" salary was estimated to be $31,000, while an "automotive sales representative" salary was $65,000 and an "enterprise sales representative" was $108,000. Thus, prior to analyzing the data from the experiment, we designed the following solution for sales representative and customer service jobs:

1. We defined sales jobs as job titles with the word "Sales" in it, and customer service jobs as jobs with the phrase "Customer Service" in it. Most of these fell into the "Sales" category.
2. We created a list of keywords that were commonly associated with higher salaries, such as "senior," "analyst," "manager," "executive," "director," "engineer," and "president." We left the salary data unchanged for any job title that had one of these keywords in it (i.e., "sales manager").
3. For all remaining customer service and sales jobs, we created a range that was approximately equal to the 10^{th} and 90^{th} percentile of expected salaries for all jobs in each category. For customer service, this range was $25,000 to $45,000. For sales, the range was $20,000 to $50,000. Any job title with a salary outside of the range was assigned the minimum or maximum salary (unless it had one of the keywords in #2 above).

This rule is likely to significantly reduce measurement error and seemed appropriate for our purpose of constructing a rough proxy for job quality. When we do not trim outliers in the salary data, our point estimates are substantively very similar, but noisier.