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What Can Employers Do to Mitigate Hiring Difficulties?

Evidence from Online Job Ads*

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Summary

Difficulties in filling open job positions have been one of the most common challenges facing U.S. businesses in recent years. What can employers do to mitigate this challenge? In this paper, we study this question by analyzing time-to-fill (TTF) data for online job ads collected by Burning Glass Technologies. We use various pieces of job requirement information listed in these ads and study their relationships with TTF. First, we find that, after controlling for differences in MSA and occupation characteristics, demanding more education and requiring longer previous job experience are both associated with longer TTF. The two requirements also interact with each other. In particular, the effect of the experience requirement on TTF increases as higher education levels are required. Second, listing a larger number of desired skills (including both soft skills such as communication skills and technical skills such as Microsoft Office) tend to result in shorter TTF, at least up to a certain threshold. More skill listings might reflect the employer's higher recruitment effort and allow applicants to direct their job search more effectively, thereby resulting in shorter TTF. Last, we also find some evidence that, for some types of jobs (routine and manual jobs), offering higher wages shortens TTF.

Introduction

By most standard metrics, the U.S. labor market has improved significantly since the end of the last recession. The level of payroll employment has been above the prerecession peak since mid-2014, and it has been steadily increasing since then. Similarly, the unemployment rate, the number of jobless individuals actively looking for a job as a share of the labor force, dropped from around 10 percent right after the Great Recession to 3.5 percent as of December 2019.

As the labor market tightened, filling open job positions has become more challenging for firms. According to a survey of small businesses by the National Federation of Independent Business (NFIB), as of August 2019, 57 percent of small businesses face difficulties finding qualified applicants for their job openings. This is the highest level since the NFIB started collecting this information in 1993 and is higher than its peak level of 48 percent immediately before the Great Recession (Panel (a) Figure 1). This phenomenon is also evident in hard data. One measure of capturing the extent of hiring difficulty is the ratio between the number of new hires and the number of open positions, known as the vacancy yield. The Job Openings and Labor Turnover Survey (JOLTS) shows that the vacancy yield rose above 1.5 at the end of the Great Recession but fell dramatically to below 0.8 at the end of 2019. Importantly, the current level is even lower than its pre-Great Recession trough of around 1.2 and, in fact, the lowest since the inception of the data in the early 2000s. This suggests that the extent of increasing hiring difficulty in recent years extends beyond cyclical reasons (Panel (b) Figure 1).[1]

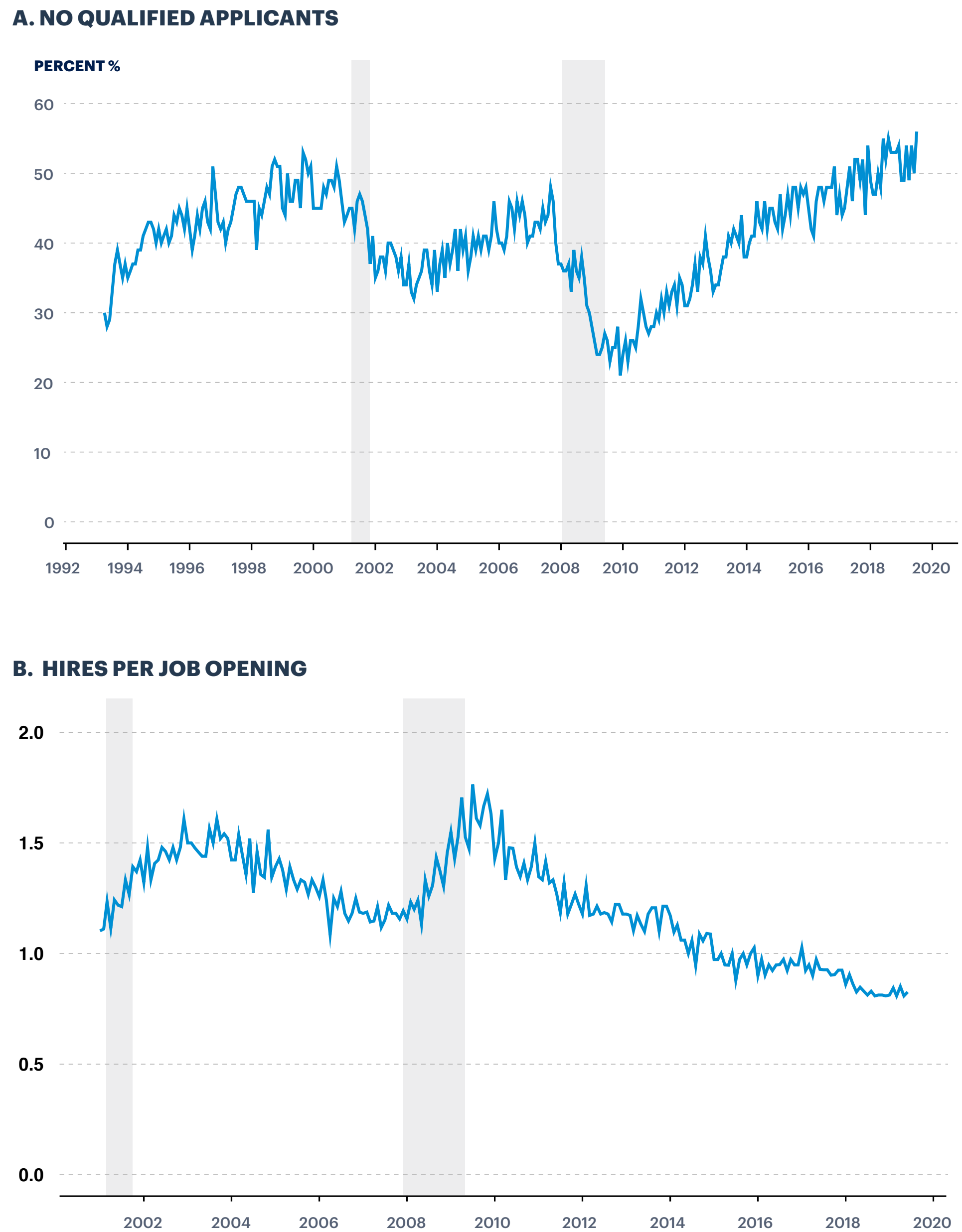
The issue of difficulty in hiring is often labeled as a skills mismatch, whereby firms cannot find workers that possess the right mix of skills and background required for the positions. The nature of that mismatch can take various forms. For example, it could be geographical: An employer in a certain location could struggle to find suitable workers for its open positions, even though such workers are available elsewhere. Another explanation could be occupational — an employer has an opening for a specific occupation, but the workers who meet the specific requirements are in short supply. The existing literature attempts to quantify the impacts of labor market mismatch on aggregate labor market measures such as unemployment rates.[2] However, the existing studies hardly look into the micro-level factors that contribute to hiring difficulties.

Using online job openings data collected by Burning Glass Technologies (BGT), we study the determinants of the time it takes to fill job openings. The main variable of our interest is the average time-to-fill (TTF) observation by every combination of the largest 50 metropolitan statistical areas (MSAs) and detailed occupation titles — a total of 720 titles, based on the Standard Occupation Classification (SOC) System — that cover the period from 2015 to 2017. The total number of underlying online job listings amounts to about 19 million. We construct corresponding job requirement variables for each MSA-by-occupation combination: (1) required education (in years), (2) required previous experience (in years), (3) skill requirement (the number of skills listed). The last variable contains information distinct from the first two variables and includes soft skills, such as leadership and communication skills, as well as technical skills, such as proficiency in Excel.

[1] The DHI-DFH measure of national mean vacancy duration (which is based on the JOLTS data and developed by Davis et al. (2013)) provides similar information and shows a similar pattern: The average number of days to fill open positions was at its highest level, at around 31 days, in April 2018. This level is much higher than the pre-Great Recession peak of around 24 days. This series is available at www.dice.com/indicators/.

[2] Barnichon and Figura (2015) construct a measure of "matching efficiency" and explore the underlying reasons for its precipitous decline at the aftermath of the Great Recession. These authors find that a large part of the decline is accounted for by the decline in the "employability" of jobless workers. Sahin et al. (2014) develop a measure called a "mismatch index," which captures the deviation of the observed distribution of jobless workers across geographical and occupational labor markets from the hypothetical "optimal" allocation of these workers. These authors find that occupational mismatches have become particularly severe for college graduates and in the West.

Figure 1. Hiring Difficulties



Panel (a): the share of small businesses reporting few of no qualified applicantsfor their job openings from National Federation of Independent Business (NFIB), Small Business Economic Trends Jobs Report. Panel (b): the number of hires divided by the number of job openings from Bureau of Labor Statistics, Job Openings and Labor Turnover Survey (JOLTS). Shaded areas represent recessions dated by the National Bureau of Economic Research (NBER).

We explore the determinants of TTF through a series of cross-sectional regressions. All regressions include MSA and occupation fixed effects to account for mean TTF differences along these two dimensions. Based on our preferred regression specification, we estimate that each additional required year of education adds about 1.7 days to TTF. In other words, demanding a college degree instead of a high school diploma raises TTF by about 7 days (or equivalently about 20 percent). Our result is in line with the claims made by several other researchers. For example, a report from Harvard Business School (Fuller and Raman (2017)) argues that employers' preference to hire college graduates is making many middle-skill jobs harder to fill.[3] Rothwell (2014) also finds that job openings in science, technology, engineering, and math (STEM) jobs take longer to fill. The author attributes the part of the hiring difficulty to the scarcity of STEM workers relative to demand.

We also study other factors affecting TTF beyond education. First, we show that requiring previous job experience contributes to longer TTF as well, especially when the experience requirement is interacted with the education requirement: For jobs requiring a bachelor's degree, requiring five years of experience (as opposed to no experience) raises TTF by about 4.5 days (or 12 percent).[4] Our result on experience requirements appears to conform with the claim made by Cappelli (2015) that increasing complaints about the lack of

[3] The authors point out the presence of a large "degree gap," defined as the difference between the share of job openings requiring a college degree or higher and the share of the existing workforce with a college degree or higher, for some occupations. They view this as the evidence that employers prefer college graduates even when the skills necessary to perform the task do not require a college degree. See also Burning Glass Technologies (2014).

[4] We do not see a statistically significant positive impact of experience requirement on TTF at lower levels of education, whereas the impact is even larger for positions requiring a graduate degree.

qualified job candidates are due to employers seeking to acquire the skills they need by hiring more experienced workers (rather than nurturing them). It is also consistent with the survey result conducted for the aforementioned Harvard Business School study that the top reason for hiring difficulty — reported by 50 percent of respondents — is the lack of sufficient work experience.

Another intriguing result is that the larger number of required skills listed is negatively associated with TTF, at least up to a certain point (after which TTF steeply rises). We interpret this evidence as indicating that listing larger number of required skills partly reflects the employer's recruiting effort, while also allowing candidates to direct their applications more effectively. Last, we examine the idea that offering higher wages helps mitigate hiring difficulties.[5] Since comprehensive wage offer information is unavailable within the BGT data set, we can examine the idea only partially, using wages for existing workers. In our baseline regression analysis, we find no statistically significant relationships between wages and TTF. However, we find that there is a large heterogeneity in the wage effect, depending on job types. That is, while higher wages are associated with longer TTF within nonroutine cognitive jobs, they are associated with shorter TTF outside nonroutine cognitive jobs. In general, each job is different not just in pay but also in many other nonpecuniary dimensions. But one can imagine that routine/manual jobs tend to be more homogenous (at least within the same occupation). If so, it is perhaps not surprising that the wage effect is more clearly identifiable within these types of jobs.

We would like to mention a few caveats about our study. In general, our regressions do not necessarily provide causal relationships between TTF and the explanatory variables. Furthermore, our analysis does not consider the returns from devoting more time and resources in the hiring process. Presumably, employers prefer more experienced or more educated candidates, because they expect these applicants to be more productive once hired (or immediately productive without training), even if it takes longer to find these workers, which implies higher (implicit and explicit) lost revenues while leaving the positions vacant. This calculus is further influenced by retention rates of these workers in the future.[6] For a more comprehensive analysis that incorporates these additional margins, we need not only more data but also a rich theoretical framework that allows us to derive more robust implications.

[5] Minneapolis Fed President Neel Kashkari suggested this in one of his interviews in 2018 (www.cnbc.com/2018/11/13/firms-trying-to-fill-jobs-should-try-paying-more-feds-kashkari-says.html).

[6] Small businesses may find it easier to hire more experienced workers during an economic downturn, but these workers may be more likely to quit later and move to larger employers as economic conditions improve.

Data

The main data set for our analysis comes from Burning Glass Technologies (BGT). The company collects near-universe data of online job openings in the U.S., drawing from about 40,000 sources, including job boards, corporate websites, and others. BGT uses proprietary algorithms to identify and remove duplicate job ads.[7] The BGT data are comparable in the industry composition with the JOLTS data, and the BGT data's occupational distribution is similar to that of BLS's Occupational Employment Statistics (OES) (Hershbein and Kahn (2018)). Included in the data set made available to us is MSA-by-occupation-level information on how long it takes to fill a job, as well as advertisement-level information on education, experience, and skill requirements for each job.

Note that the TTF observations are available only as the MSA-by-occupation averages. All analysis therefore has to be aggregated into the MSA-by-occupation level. Note also that the TTF data are based on the subset of the underlying BGT ad data. The underlying number of ad counts included in the TTF data suggest that the TTF data cover roughly 80 percent of the original BGT data. In our analysis, each TTF observation is weighted by ad counts in each MSA-by-occupation cell. Each job is classified into one of more than 700 detailed titles based on the Census Bureau's 2010 Standard Occupational Classification (SOC) System.[8] Our analysis focuses on the 50 largest MSAs in the U.S. from 2015 to 2017.[9]

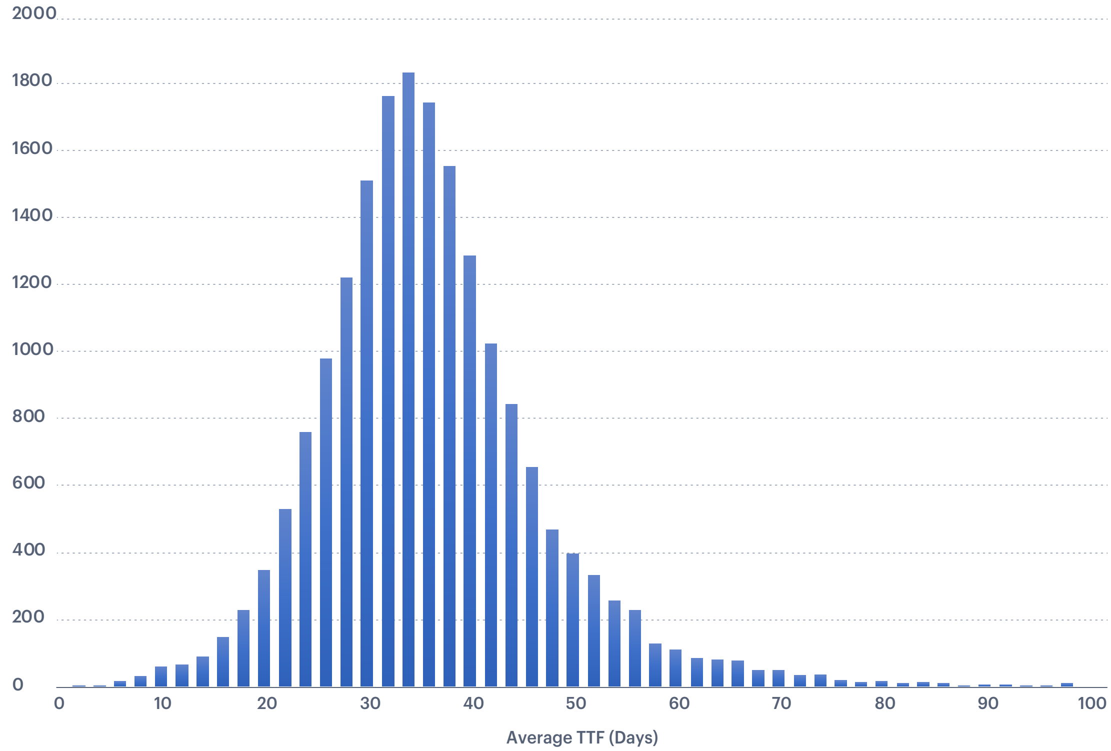
The primary variable of interest, TTF, is defined as the average difference between job ads' posting and removal dates. BGT includes only the job ads from employer websites, and this sample restriction is adopted to mitigate biases caused by contracts for job boards. More specifically, some ads, such as those on LinkedIn, may not be removed immediately after the position is filled and stay on for the full period of the contract between the employer and LinkedIn.

[7] See, for example, Carnevale et al. (2014) for the basic description of the data such as the accuracy and the sample characteristics. Note that the data quality has improved over time. For example, the share of online job openings in the BGT data is roughly 85 percent of the job openings in JOLTS data in 2016 (Azar et al. (2018)).

[8] The codes always correspond to the first six digits of a job's O*NET code, and BGT uses the 2010 SOC.

[9] The MSA definition in both the BGT and OES data takes the 2013 MSA definition for most of the country, except when an area is also defined by a New England city and town area (NECTA), in which case the NECTA takes precedence over the MSA. For example, a job in Boston would be represented by NECTA 71650 instead of MSA 14460.

Figure 2. Distribution of the Time to Fill



Source: Burning Glass Technologies. Notes: Based on MSA-by-Occupation (19,182) observations weighted by underlying number of ads. Mean: 37.2 days; SD: 11.4 days; Min: 3 days; Max: 175 days. The histogram is truncated at 100 days.

Characteristics of TTF Data

Before examining the possible determinants of TTF, we briefly summarize the characteristics of our data.

In Figure 2, we plot the histogram of the TTF data. This histogram is based on a total of 19,000 MSA-by-occupation observations. As noted previously, our data cover the period from 2015 to 2017. Each of our MSA-by-occupation observations represents the weighted average across those three years. All of our analyses that follow use average observations across these three years, focusing on cross-sectional relationships.[10] On average, it takes about 37 days to fill an open position, with a standard deviation of about 11 days. The average duration in our data is somewhat longer than the aforementioned DHI-DFH measure of average vacancy duration. The latter measure is based on the JOLTS data and is thus a nationally representative sample. Although the coverage of the BGT data itself is considered quite high, the TTF data are based on a subset of these BGT data. Thus, the difference in mean durations may reflect the remaining difference in the sample characteristics of the BGT/TTF data.[11] But the difference in mean durations is not alarmingly large.

In Table 1, we rank the 50 largest MSAs by their average TTF over all occupations. The first column gives the (raw) ranking, and the second column gives the corresponding raw average TTF. A quick glance at the bottom two MSAs in the first column (San Jose-Sunnyvale-Santa Clara, CA and Seattle-Tacoma-Bellevue, WA) may suggest that the ranking reflects technology-related jobs taking longer to fill, but a broader look at the table suggests this is not necessarily the case. In general, variations of TTF across MSAs could result from different distributions of jobs across MSAs differ with respect to difficulties of filling open positions. For example, the average time it takes to fill job openings in a city with a large number of jobs requiring some specific knowledge/skills is likely to be longer. However, as discussed later with respect to the "adjusted" ranking, the difference in job composition does not account for the difference in the average TTF across MSAs.

[11] The JOLTS job openings data do not offer occupation breakdowns, while our BGT/TTF data are organized by occupation-by-MSA cells without industry breakdowns. We thus cannot formally assess the extent of the sample selection of the TTF data.

Table 1. MSAs Ranked by Time to Fill

Raw Rank	Raw TTF (days)	Adjusted Rank	Adj. TTF (days)	MSA
1	29.55	2	30.26	Salt Lake City, UT
2	29.84	1	29.67	Denver-Aurora-Lakewood, CO
3	31.62	3	31.09	Las Vegas-Henderson-Paradise, NV
4	31.95	4	32.15	Jacksonville, FL
5	32.52	5	32.68	Phoenix-Mesa-Scottsdale, AZ
6	32.75	6	33.13	Des Moines-West Des Moines, IA
7	33.10	7	33.25	Columbus, OH
8	33.23	8	33.51	Virginia Beach-Norfolk-Newport News , VA-NC
9	34.38	12	34.71	Miami-Fort Lauderdale-West Palm Beach, FL
10	34.55	13	34.83	Tampa-St. Petersburg-Clearwater, FL
11	34.57	11	34.53	Charlotte-Concord-Gastonia, NC-SC
12	34.59	10	34.52	Orlando-Kissimmee-Sanford, FL
13	34.70	9	34.43	Houston-The Woodlands-Sugar Land, TX
14	35.02	21	35.36	Kansas City, MO-KS
15	35.02	15	34.91	Portland-Vancouver-Hillsboro, OR-WA
16	35.06	16	34.92	Austin-Round Rock, TX
17	35.14	19	35.27	Minneapolis-St. Paul-Bloomington, MN-WI
18	35.20	18	35.15	San Antonio-New Braunfels, TX
19	35.33	14	34.9	Cleveland-Elyria, OH
20	35.40	20	35.31	Atlanta-Sandy Springs-Roswell, GA
21	35.51	17	35.06	Detroit-Warren-Dearborn, MI
22	35.55	24	35.81	Milwaukee-Waukesha-West Allis, WI
23	35.59	22	35.62	Dallas-Fort Worth-Arlington, TX
24	35.60	23	35.69	Richmond, VA
25	35.85	26	36.14	Memphis, TN-MS-AR
26	36.01	25	36.09	Riverside-San Bernardino-Ontario, CA
27	36.10	27	36.24	Omaha-Council Bluffs, NE-IA
28	36.18	29	36.39	Cincinnati, OH-KY-IN
29	36.21	28	36.38	Birmingham-Hoover, AL
30	36.62	32	37.00	Nashville-Davidson–Murfreesboro–Franklin, TN
31	36.87	30	36.77	San Diego-Carlsbad, CA
32	36.88	34	37.42	Louisville/Jefferson County, KY-IN
33	37.08	31	36.91	Raleigh, NC
34	37.25	33	37.13	Sacramento–Roseville–Arden-Arcade, CA
35	37.36	35	37.45	St. Louis, MO-IL
36	37.63	36	37.52	Hartford-West Hartford-East Hartford, CT
37	37.84	38	38.27	Indianapolis-Carmel-Anderson, IN
38	37.87	37	37.9	Providence-Warwick, RI-MA
39	38.35	39	38.36	Washington-Arlington-Alexandria, DC-VA-MD-WV
40	38.52	40	38.67	Chicago-Naperville-Elgin, IL-IN-WI
41	39.05	43	39.21	Los Angeles-Long Beach-Anaheim, CA
42	39.13	41	39.12	Boston-Cambridge-Nashua, MA-NH
43	39.16	42	39.17	New York-Newark-Jersey City, NY-NJ-PA
44	39.43	45	39.56	Baltimore-Columbia-Towson, MD
45	39.46	46	39.72	San Francisco-Oakland-Hayward, CA
46	39.51	44	39.33	Bridgeport-Stamford-Norwalk, CT
47	41.49	48	41.36	Philadelphia-Camden-Wilmington, PA-NJ-DE-MD
48	41.59	49	41.70	Pittsburgh, PA
49	41.69	47	41.10	Seattle-Tacoma-Bellevue, WA
50	43.83	50	43.09	San Jose-Sunnyvale-Santa Clara, CA

Table 2. Top-20 Easiest-to-Fill Occupations

Occupation	SOC Code	Average TTF	Type
Farm Labor Contractors	131074	3.00	F
Probation Officers and Correctional Treatment Specialists	211092	17.14	NRC
Radio, Cellular, and Tower Equipment Installers and Repairs	492021	19.64	RM
Explosives Workers, Ordnance Handling Experts, and Blasters	475031	21.80	RM
Tile and Marble Setters	472044	22.02	RM
Correctional Officers and Jailers	333012	22.45	NRM
Airline Pilots, Copilots, and Flight Engineers	532011	22.99	RM
Drywall and Ceiling Tile Installers	472081	23.14	RM
Court, Municipal, and License Clerks	434031	23.16	RC
Tank Car, Truck, and Ship Loaders	537121	23.33	RM
Geographers	193092	23.46	NRC
Legal Secretaries	436012	23.59	RC
Railroad Conductors and Yardmasters	534031	23.84	RM
Physical Therapist Aides	312022	23.87	NRM
Human Resources Assistants, Except Payroll and Timekeeping	434161	23.98	RC
First-Line Supervisors of Police and Detectives	331012	24.00	NRM
Data Entry Keyers	439021	24.14	RC
Library Assistants, Clerical	434121	24.24	RC
Bookkeeping, Accounting, and Auditing Clerks	433031	24.64	RC
Helpers–Carpenters	473012	24.68	RM

Source: Burning Glass Technologies. Notes: RM: routine manual, NRM: nonroutine Manual, RC: routine cognitive, NRC: nonroutine cognitive, F: farming.

Table 3. Top-20 Hardest-to-Fill Occupations

Occupation Name	SOC Code	Average TTF	Type
Art, Drama, and Music Teachers, Postsecondary	251121	105.87	NRC
Refuse and Recyclable Material Collectors	537081	89.39	RM
Veterinarians	291131	75.5	NRC
Insulation Workers, Floor, Ceiling, and Wall	472131	72.78	RM
Foreign Language and Literature Teachers, Postsecondary	251124	68.85	NRC
Optometrists	291041	64.62	NRC
Veterinary Assistants and Laboratory Animal Caretakers	319096	63.35	NRM
Speech-Language Pathologists	291127	62.11	NRC
Pediatricians, General	291065	60.54	NRC
Animal Trainers	392011	59.44	NRM
Anesthesiologists	291061	58.39	NRC
Psychology Teachers, Postsecondary	251066	58.23	NRC
Psychiatrists	291066	58.12	NRC
Nonfarm Animal Caretakers	392021	56.72	NRM
Genetic Counselors	299092	56.3	NRC
Family and General Practitioners	291062	56.25	NRC
Biological Science Teachers,Postsecondary	251042	54.66	NRC
Agricultural Equipment Operators	452091	53.94	F
Clinical, Counseling, and School Psychologists	193031	53.64	NRC
Teachers and Instructors, All Other	253099	53.34	NRC

Source: Burning Glass Technologies. Notes: RM: routine manual, NRM: nonroutine manual, RC: routine cognitive, NRC: nonroutine cognitive, F: farming.

In Tables 2 and 3, we slice the data by occupation (instead of by MSA) and present the 20 easiest and hardest jobs (occupations) to fill, respectively. To ease the interpretation, we also present in the last column a brand of a more coarse occupational classification system suggested by Autor et al. (2003), which classifies jobs on a two-way scale as either routine or nonroutine, and either manual or cognitive (farming and military jobs are categorized separately).[12] One can see that routine occupations tend to make up the top-20 easiest-to-fill occupations, while the top-20 hardest-to-fill occupations are disproportionately nonroutine.

One can also observe that variations in TTF by occupation is much larger, ranging from shorter than 20 days to longer than 100 days, than those by MSA, which range from 30 to 43 days. The smaller variations in TTF across MSAs suggest that the composition of occupations across MSAs is relatively similar.

We can formally adjust for the difference in the occupation composition across MSAs through the following regression, with MSA (MSA_i) and occupation (occ_j) fixed effects:

$$TTF_{ij} = MSA_i + occ_j + e_{ij}, \qquad (1)$$

where e_{ij} represents the error term. This regression allows us to extract variations of TTF only accounted for by the MSA fixed effects, while keeping the occupation composition across MSAs the same at the overall composition. The updated ranking

[12] Cortes et al. (2014) present the mapping from the detailed occupation codes into the broad groups. We use the mapping presented in Table A.1 of their paper. In putting together Tables 2 and 3, we excluded cases where either (1) the number of ads of a particular occupation is fewer than 100 or (2) the openings for the occupation appear only in a small number of MSAs (more specifically fewer than five).

Figure 3. Histograms of Explanatory Variables

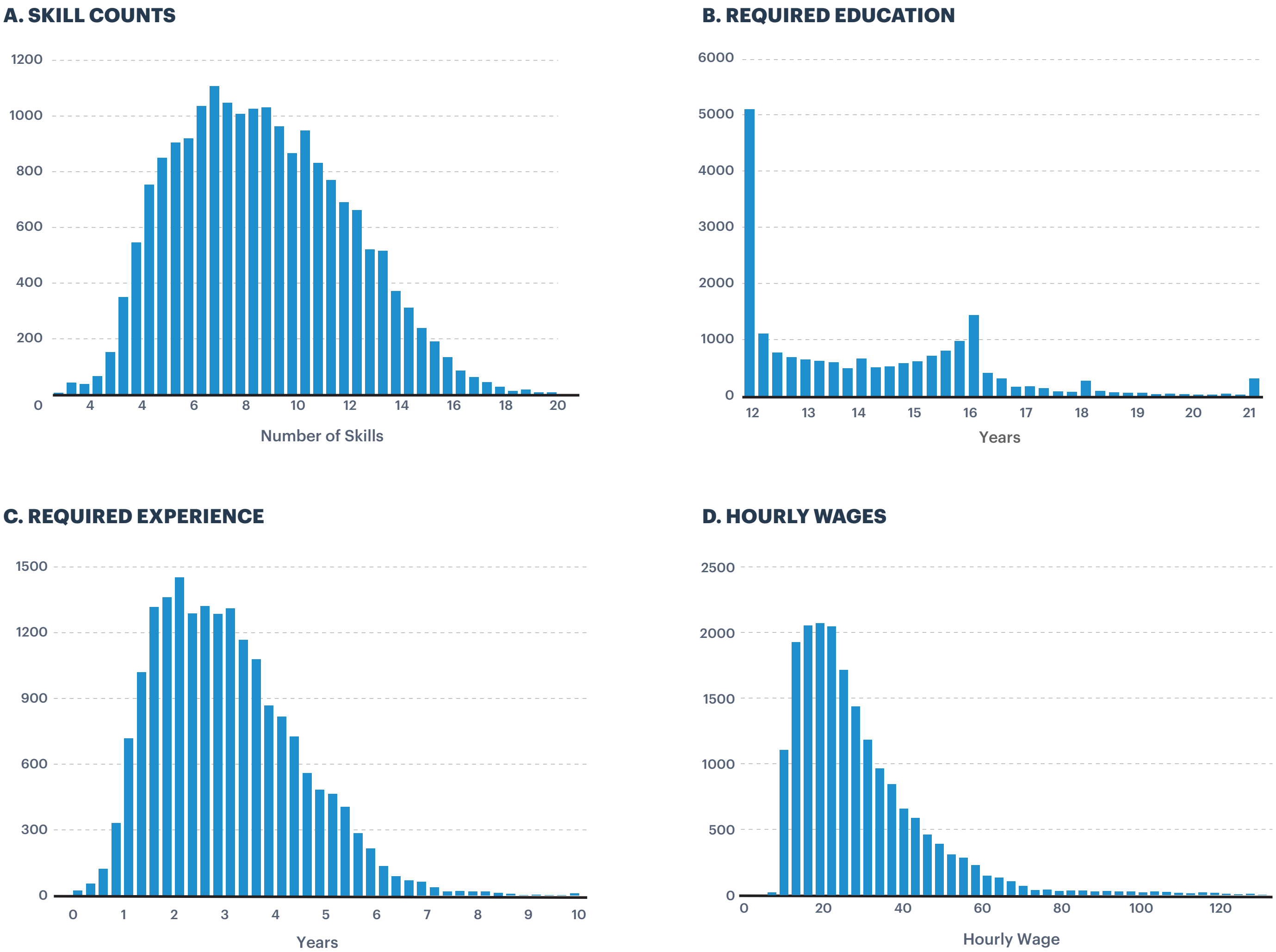


Table 4. Top-20 Required Skills

Rank	Required Skill	(%)
1	Communication Skills	30.77
2	Customer Service	15.85
3	Teamwork/Collaboration	14.57
4	Organizational Skills	12.79
5	Microsoft Excel	12.57
6	Sales	12.24
7	Problem Solving	11.67
8	Planning	10.79
9	Detail-Oriented	10.29
10	Scheduling	10.29
11	Writing	9.96
12	Microsoft Office	9.84
13	Research	9.42
14	Computer Literacy	8.74
15	Physical Abilities	8.50
16	Budgeting	7.83
17	Building Effective Relationships	7.79
18	Written Communication	7.37
19	Project Management	7.34
20	Creativity	6.42

Source: Burning Glass Technologies. The third column (%) represents the frequency of each skill appearing in online job ads.

and corresponding adjusted average TTF are presented in the third and fourth columns of Table 1. Although there are some MSAs, such as Kansas City, that change rank significantly, the overall ranking remains very similar, even after controlling for the differences in the occupational composition.

Job Requirements and TTF
Construction of the Requirement Variables

We now study how TTF is related to various characteristics of job ads. We construct the average years of required education and experience for each occupation-by-MSA combination from our ad-level BGT data. Recall that our TTF data are aggregated in to occupation-by-MSA combinations. Also, not all ads include these pieces of information. In constructing the two variables, we drop the observations (ads) that are missing education or experience requirements. An alternative is to take missing information as "no requirement" and impute a missing experience requirement as 0 and a missing education requirement as 12 years. A quick inspection of the data, however, clearly indicates that this practice is misleading.[13] Our treatment of dropping these observations implies that these pieces of information are missing at random. In other words, the distributions of underlying experience and education requirements (of the ads missing these pieces of information) are the same as those of the observed ones. There are cases that explicitly state that there is no experience requirement, and they are treated as such. In our regressions, we use our education requirement variable (measured in years) as a continuous variable.[14]

We construct two more variables to be included in our regressions. First, we compute the average number of skill requirements for each MSA-occupation combination, using ad-level observations in the BGT data.[15] Table 4 lists the top-20 skills in our data. This list includes both soft skills, such as communication skills, teamwork, and management, as well as technical skills, such as Microsoft Excel and computer skills. It is important to note that this variable captures the information distinct from our experience and education requirement variables.

Last, our regressions include average wages for occupation-by-MSA combinations. Ideally, we would have liked to directly obtain ad-level wage offer information from the BGT data. However, that information is available only for a small subset of the ads. We thus use average wages of existing workers for all MSA-occupation combinations, taken from the OES database. We compute average wages over the same period (2015–2017) as in our TTF data. The OES database covers the

Table 5. Summary Statistics of Requirement Variables and Average Wages

	Mean	SD	Min	Max
TTF (Days)	37.19	11.36	3	175
Skill Counts	8.62	3.30	0	27
Required Education (Yrs)	14.18	2.08	12	21
Required Experience (Yrs)	3.04	1.40	0	15
Hourly Wage ($)	28.93	16.66	8.6	136.2

Source. Burning Glass Technologies, Bureau of Labor Statistics (Metropolitan Area Occupational Wage Estimates).

Table 6: Determinants of TTF

	Dependent Variable: Average TTF			
	(i)	(ii)	(iii)	(iv)
Skill Counts	-0.2116**	-0.5292***	-0.5494***	2.2265***
	(0.1049)	(0.0603)	(0.060)	(0.4413)
Skill Counts^2				-0.3762***
				(0.0425)
Skill Counts^3				0.0142***
				(0.014)
Required Education (Yrs)	-0.0716	1.3868***	0.3557	0.5860**
	(0.3941)	(0.1848)	(0.2459)	(0.2557)
Required Experience (Yrs)	0.4222**	0.5137***	-5.9503***	-4.5405***
	(0.1809)	(0.1780)	(0.8932)	(0.9441)
Education x Experience			0.4346***	0.3394***
			(0.0580)	(0.0603)
log(Wage)	0.9494	1.2708	0.9279	1.1428
	(1.5471)	(1.1656)	(1.1443)	(1.1849)
Occupation fixed effects	6-digit	4-digit	4-digit	4-digit
MSA fixed effects	✓	✓	✓	✓
$\hat{R}^2$	0.6199	0.4745	0.4789	0.4896
N	19,182	19,182	19,182	19,182

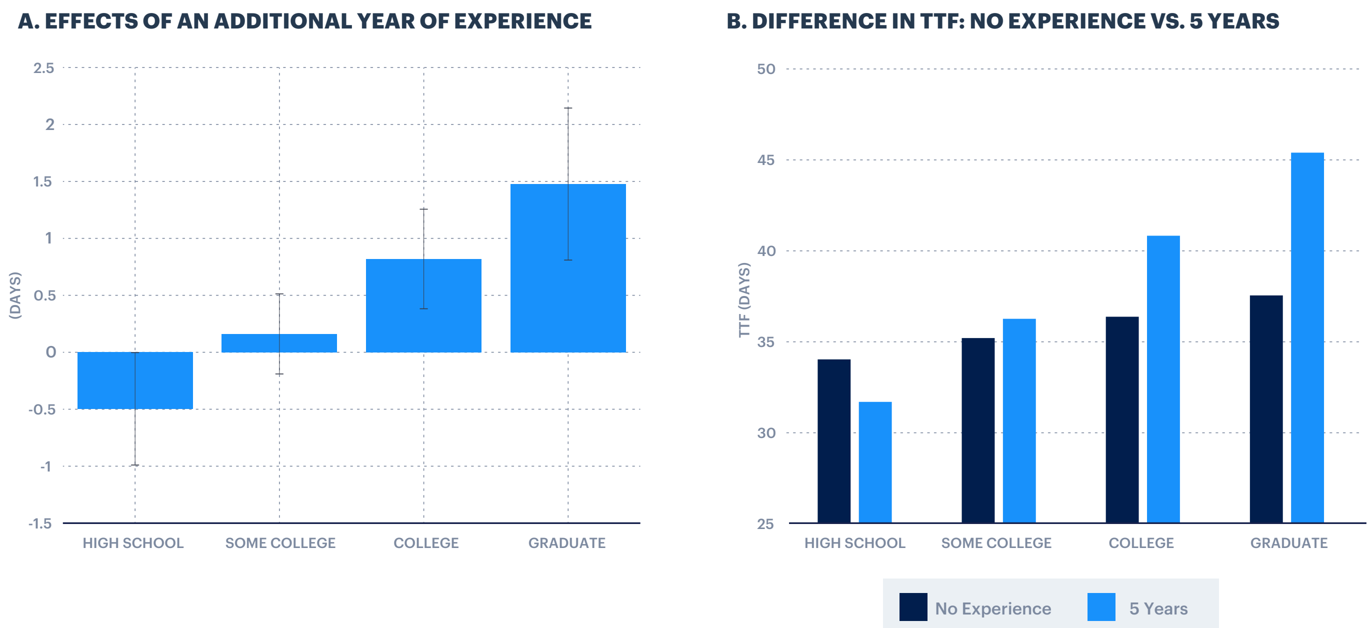
Notes: *,**, and *** indicate statistical significance at 10%, 5%, and 1%, respectively. Heteroscedasticity consistent standard errors are in parenthesis.

[13] For example, we observe many job postings for attorneys without any education requirement.

[14] We treat the education requirement variable as a continuous variable because each observation in our dataset is an average within each MSA-occupation combination. We also considered the specification in which this variable is recategorized into four education groups. Our regression results are robust with respect to this alternative treatment of education requirement.

[15] This list is canonicalized so that we are not double counting skills that are almost identical. For example, Python 3.3 and Python 2.7 are both standardized to Python.

Figure 4: Effects of Required Experience on TTF by Education



Notes: Error bars in Panel (a) represent 95% confidence intervals. Based on regression (iv) in Table 6.

same 50 MSAs and the same detailed occupation (SOC) codes. Roughly 7 percent of observations of all occupation-by-MSA-by-year combinations for which TTF observations are available are missing. We therefore impute those missing wage observations by running a wage regression with MSA, occupation, and year fixed effects. These fixed effects account for 95 percent of variations of average wages across those three dimensions.

Figure 3 plots the histograms of the four variables, and Table 5 presents their summary statistics. On average, firms list roughly eight skills for each job ad, with a standard deviation of about three skills. The average experience requirement is three years, with a standard deviation of 1.4 years, while the average education requirement is 14.2 years, with a standard deviation of two years. The average hourly wage is about $29, with a standard deviation of $17. These variables enter the regressions after being weighted by the underlying number of ads in TTF data.

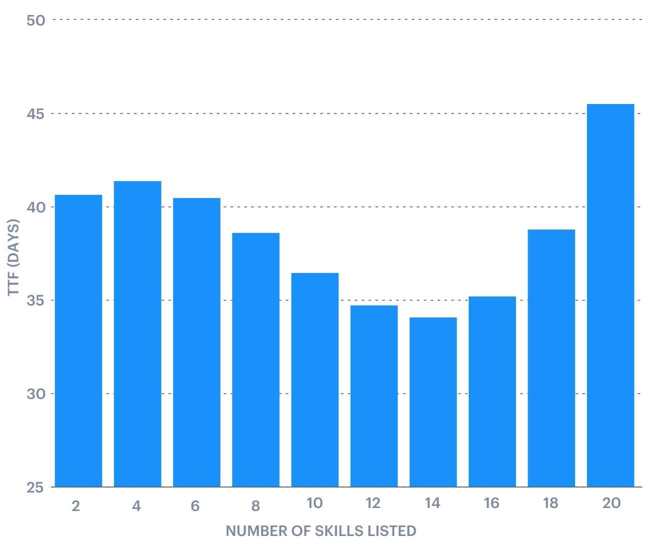
Regression Results

Table 6 presents the results from four different regressions. Specification (i) adds the four variables linearly to the one we estimated before, Equation (1). Under this specification, the number of skills listed has a small but statistically significant negative effect on TTF, the experience requirement is associated with an increase in TTF, and coefficients on required education and log wage are not statistically different from zero.

A key issue with this specification, however, is that, since the occupation fixed effects enter this regression at the same level of disaggregation as the underlying observations, it does not allow for variations in TTF within the same occupation and MSA. To get around this problem, while also accounting for TTF differences due to occupation characteristics, the second specification uses the occupation fixed effects at the four-digit level. Using four-digit codes reduces the number of titles to 110. This specification allows us to exploit within-occupation variations in TTF and the explanatory variables, even within the same MSAs. From here on, we define the occupation fixed effects at the four-digit level. Specification (ii) simply replaces the six-digit occupation fixed effects with the four-digit occupation fixed effects. Under this specification the effect of skill counts remain negative, but the impact increases. The coefficient on education turns positive and is now highly significant. The point estimate indicates that requiring a bachelor’s degree instead of a high school diploma extends TTF by about five to six days. The coefficient on the experience requirement is positive and increases somewhat from the previous case.

Specification (iii) allows for the possibility that the effect of required experience depends on the level of education. We indeed find that the coefficient on the interaction term is positive and highly significant. The estimated coefficients indeed imply that the effects of the experience requirement on TTF tend to increase as the education requirement rises (we will discuss this more specifically later). The coefficient on skill counts remains negative and thus robust. Our interpretation for this

Figure 5: Effects of Skill Counts on TTF



Notes: Based on regression (iv) in Table 6.

Table 7. Summary Statistics by Occupation Type

	Counts	Mean	SD	Min	Max
RM					
TTF (Days)	4,312	36.0	11.1	5.0	175.0
Skill Counts	4,312	6.7	2.5	0.0	20.7
Required Education (Yrs)	4,312	12.4	0.7	12.0	17.4
Required Experience (Yrs	4,312	2.8	1.3	0.1	15.0
Hourly Wage	4,312	21.0	7.4	9.2	70.1
RC					
TTF (Days)	2,760	31.8	8.0	7.0	98.0
Skill Counts	2,760	8.8	2.4	1.3	25.0
Required Education (Yrs)	2,760	13.2	1.0	12.0	17.0
Required Experience (Yrs)	2,760	2.4	1.0	0.2	9.1
Hourly Wage	2,760	21.2	9.0	9.2	75.7
NRM					
TTF (Days)	2,570	39.4	11.9	6.0	120.0
Skill Counts	2,570	6.3	2.4	0.0	25.1
Required Education (Yrs)	2,570	12.6	0.9	12.0	18.0
Required Experience (Yrs)	2,570	1.9	1.0	0.1	12.5
Hourly Wage	2,570	16.5	7.4	8.6	69.4
NRC					
TTF (Days)	9,472	38.7	11.6	3.0	132.0
Skill Counts	9,472	10.1	3.3	1.1	27.1
Required Education (Yrs)	9,472	15.7	1.8	12.0	21.0
Required Experience (Yrs)	9,472	3.6	1.4	0.1	11.0
Hourly Wage	9,472	38.2	18.0	11.5	136.2

Source: Burning Glass Technologies, Bureau of Labor Statistics (Metropolitan Area Occupational Wage Estimates).

Notes: RM: routine manual, NRM: nonroutine manual, RC: routine cognitive, NRC: nonroutine cognitive.

result is that listing more necessary skills makes the "matching" process more efficient. For example, ads that are more explicit about necessary skills allow the potential candidates to direct their job searches more effectively and efficiently. It may also work as an initial screening device by deterring unqualified candidates, thereby speeding up the hiring process. Another possibility is that this variable reflects the employer's readiness or preparedness to select appropriate individuals.

In specifications (i) through (iii), skill counts enter linearly in the regressions. But obviously, the impact of skill counts on TTF cannot always be negative for any number of skills listed. It is likely that adding more skills at some point works against shortening TTF. The last specification (iv) allows for this nonlinear effect by adding the square and cubic terms to specification (iii). Under specification (iv), the nonlinear terms of skill counts are both highly significant. As shown below, the estimated coefficients indeed imply that listing more skills starts having the adverse effect on TTF, once skill counts exceed a certain threshold. All other coefficients except for the one on wages are statistically significant. Regarding the wage effect, none of the four specifications reveal the pattern that higher wages are associated with shorter TTF. In the analysis below, however, we show that there is substantial heterogeneity once we split the sample, based on broad occupation types.

Figure 4 graphically summarizes the effects of required years of experience on TTF broken down by education. The results are based on specification (iv). Panel (a) presents the average marginal effect of asking for one more year of prior job experience at four education levels.[16] Panel (b) presents predicted TTF at "no experience requirement" and "five years of experience" by the same four education levels. We can see that the effects of the experience requirement on TTF are concentrated among job openings requiring high levels of education. For the positions requiring a college education, asking for five years of previous experience, instead of asking for no experience, increases TTF by about 15 percent. The effect increases to 20 percent for job openings requiring graduate degrees.

[16] As noted previously, the education requirement variable enters the regressions as a continuous variable. We evaluate the regression results at four education levels: 12 years (high school), 14 years (some college), 16 years (college), and 18 years (graduate).

Table 8: Average Marginal Effects on TTF by Job Type

	RM/RC/NRM	NRC
Skill Counts	-0.162**	-0.641***
	(0.075)	(0.077)
Required Education (Yrs)	0.048	1.191***
	(0.290)	(0.244)
Required Experience (Yrs)	0.284	0.711***
	(0.185)	(0.245)
log(Hourly Wage)	-3,769***	4,642***
	(0.614)	(1.681)
N	9,642	9,472
R^2	0.588	0.450

Notes: Marginal effects are based on specification (iv) in Table 6, estimated separately for the two broad occupation types. *,**, and *** indicate statistical significance at 10%, 5%, and 1%, respectively. Heteroscedasticity consistent standard errors are in parenthesis.

Figure 6: Effects of Required Experience on TTF by Job Type

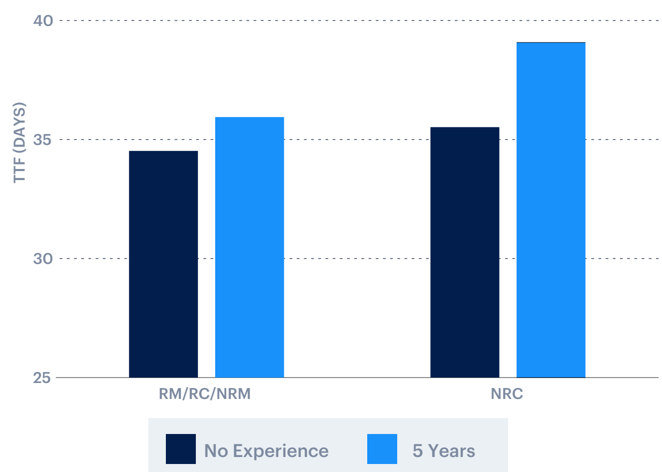


Figure 5 presents predicted TTF by the number of skills listed. TTF remains roughly the same up to around six skills, but then falls significantly up to around 14 skills, from which point adding more skills increasingly raises TTF.

Results by Occupation Types

Our previous regressions are based on pooled MSA-by-occupation observations. However, it is possible that the effects of the explanatory variables can differ across different occupation types. As we saw before (Tables 2 and 3), there appears to be a systematic difference in TTF with respect to the two-way scale classifications. In Table 7, we present summary statistics of the five variables by the four broad occupation types. In terms of TTF, the average for routine cognitive jobs is noticeably shorter, whereas, in the other four dimensions, nonroutine cognitive jobs clearly stand out: their average skill counts are the highest, they tend to require more education and job experience, and their average wages are much higher than the other three job categories. In the current section, we split the sample into two groups — one for routine manual, routine cognitive, and nonroutine manual (RM/RC/NRM) occupations, and the other for nonroutine cognitive (NRC) occupations — and separately estimate the same regression as previously. The sample sizes of the two groups are roughly equal (9,642 vs. 9,472); the former group includes 67 four-digit level occupations, while the latter group includes 37 four-digit level occupations.

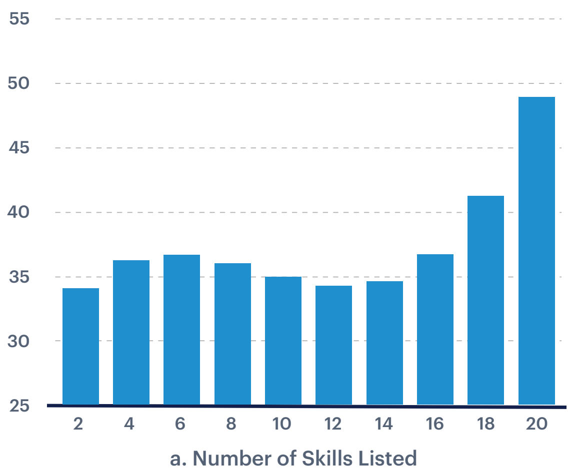
Here, we focus on the results from specification (iv) that features the interaction terms between the education and experience requirements and the nonlinear effects of skill counts.[17] Table 8 summarizes the regression result by presenting the average marginal effects of the four variables of our interest on TTF. First, the effects of the education and experience requirements for RM/RC/NRM jobs largely disappear, while those for NRC jobs remain strong. In Figure 6, we present predicted TTF for the two types of jobs at no experience requirement and at five years of experience. As the marginal effects indicated, TTF is similar at both levels of experience requirement for RM/RC/NRM jobs, and the difference is not statistically significant. On the other hand, the effect of experience requirement for NRC jobs is much more noticeable and statistically significant. This pattern is consistent with the nonlinear effects of experience requirement interacting with the education requirement in our baseline regression (as presented in Figure 4), because the education requirement is much higher for NRC jobs.[18] For both types of jobs, skill counts on average have negative effects on TTF, as in the baseline regression. But, as Figure 7 shows, the nonlinear effects are more visible within NRC jobs. Within RM/RC/NRM jobs, some reduction in TTF is observed in the range from six to 12 skills, but the gain is relatively small. Within NRC jobs, the reduction in TTF occurs monotonically through 12 skills and is quantitatively large.

[17] Note that required education and occupation types are highly correlated. For example, less than 1 percent of nonroutine cognitive jobs have an education requirement of 12 years. Thus, dropping the education variable does not materially change the results.

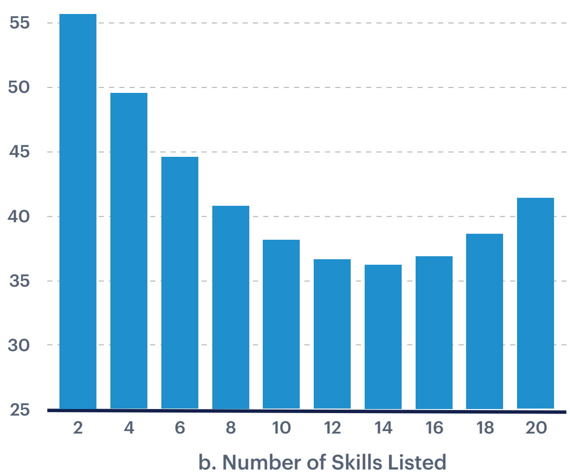
[18] Within NRC jobs, we do not find a clear nonlinear effect between the experience and education requirements, whereas the nonlinear effect remains within RM/RC/NRM jobs but is weaker than before.

Figure 7: Effects of Skill Counts on TTF by Job Type

A. RM/RC/NRM



B. NRC



Recall that the relationships between wages and TTF were statistically insignificant across all specifications we considered when we pooled all MSA-by-occupation observations. However, estimating the regressions separately for the two types of jobs reveals a large heterogeneity in the wage effect between the two broad occupation types. Even though our wage series are not taken directly from the underlying ads, the wage's negative marginal effect within RM/RC/NRM jobs is consistent with the idea that offering higher wages facilitates filling job openings. For NRC jobs, the relationship is completely flipped. We believe that this contrasting pattern is quite intuitive. Generally speaking, jobs are heterogeneous not only with respect to pay but also with respect to various nonpecuniary aspects and tasks involved. However, we can imagine that the RM/RC/NRM types are more homogeneous in terms of tasks and nonpecuniary aspects; therefore, wages play a more dominant role in the overall value of the job (which includes both pecuniary and nonpecuniary values) than they do for NRC jobs. If so, it is not surprising that the underlying wage effect on TTF is picked up more clearly within RM/RC/NRM jobs. On the other hand, the positive relationship for NRC jobs could be because wage information captures nuanced heterogeneities of jobs that are positively correlated with difficulties in finding suitable workers, thereby hiding the underlying effect of reducing TTF. Observe also that R^2 is more than 14 percent higher for the former types, i.e., fixed effects and observable characteristics explain much larger part of variations in TTF for RM/RC/NRM jobs. This result is in line with our interpretation that these jobs are more homogeneous compared with NRC jobs.

Conclusion

In this paper, we studied the determinants of TTF, using online job openings data assembled by Burning Glass Technologies. In particular, we examined the extent to which hiring difficulty, measured by longer TTF, is associated with the observable characteristics of those online job ads. Overall, we find that education and experience requirements have statistically significant positive impacts on TTF and that these two requirements interact with each other. We also uncover a strong nonlinear effect of skill counts on TTF: TTF tends to fall as skill counts increase, up to a certain threshold. Last, we show that there is a negative relationship between wages and TTF at least for some types of jobs (manual and routine jobs).

As noted in the introduction, this paper is meant to provide a basic statistical summary of the TTF data. We thus have to be cautious about interpreting our results as causality and drawing strong policy implications. Nevertheless, this paper provides the first empirical evidence that calls for a reconsideration of current hiring practices. For instance, finding more experienced workers takes more time, especially for jobs requiring higher levels of education, or equivalently, for nonroutine cognitive jobs. Natural alternatives would be to hire less experienced workers and train them or to promote existing workers internally.[19] The evidence on skill counts points to a potential route for reducing TTF as well. More generally, the careful crafting of job ads with respect to skill requirements can help improve "match quality" and is thus also likely to increase retention rates. ■

[19] A well-known challenge of employer-sponsored general training is that it increases the worker's productivity not just within the firm but also elsewhere, raising the concern that the firm loses the worker before capturing the full benefits. The literature provides some theoretical explanations as to why firms nevertheless are willing to invest in their workers' general human capital (see for example, Acemoglu and Pischke (1998, 1999)). However, empirical work on the prevalence and effectiveness of employer-sponsored training is not abundant, largely because of the lack of recent comprehensive data on training. Given this tension, there appear to be some justifications for various government-sponsored training programs.

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