Hiring in Online Labor Markets: The Role of Job-specific Experience

Completed Research Paper

Ashish Kabra
University of Maryland
7621 Mowatt Ln
College Park, MD 20742
United States
akabra@rhsmith.umd.edu

Qingchen Wang
University of Hong Kong
K.K. Leung Building
Pok Fu Lam Rd
Hong Kong SAR, China
qcwang@hku.hk

Abstract

This paper investigates the role of workers' job-specific experience on employers' hiring decisions in online labor markets. Relying on textual descriptions of job postings and natural language processing techniques, we design a novel metric that measures how well a worker's past experience fits the requirements of a specific job. We show that our job-specific experience metric is a significant predictor of whether the employee will be hired for each specific job, even when accounting for observable worker- and job-level idiosyncratic factors and overall market competition.

Keywords: Online labor markets, labor economics, job-specific experience, text mining

Introduction

With the rise of technology, the workplace is shifting from office to home, and the 9-to-5 job is being shunned in favor of freelancing. According to a 2018 survey by Freelancing In America, 35% of workers in the U.S. are freelancing, contributing more than $1.4 trillion to the economy. The rise in freelancing is mirrored by a rise in online labor markets (OLMs), which, as an online marketplace, facilitates the matching of supply and demand for freelance labor. Similar to most other online marketplaces, OLMs support freelancing by providing information about buyers and sellers through verifying profiles and serving as a third-party mediator for disputes. However, unlike other marketplaces such as ride-hailing and room-sharing, there is considerably more heterogeneity in the buyers' needs and the sellers' offerings, leading to significant challenges in obtaining satisfactory matches for both sides. In a marketplace for exact services such as ride-hailing or manufactured products such as e-commerce, buyers know exactly what they need (e.g., a ride from location A to location B) and sellers know exactly whether or not they are able to satisfy buyers' needs. Consequently, finding the right price is all that is necessary to satisfy both sides. However, in markets for freelancing labor, buyers and sellers are not clear about their needs and offerings, thus significant effort is required to consult additional information and infer the quality of potential matches.

By better understanding the drivers of matches, OLMs can design new mechanisms and improved recommendation systems to boost match quality and efficiency. This is important because match rates for OLMs are often low—the fraction of job postings by the buyer side that ends up in selecting a seller is only around 40%, despite the fact that there exist many sellers who can be good matches for the job. We posit that this is due to the high search costs incurred from the uncertain requirements, open-ended job posts and the resulting inability for sellers to identify and meet such requirements. A number of papers have studied various aspects of OLMs and identified a number of drivers that play a role in matches, including availability (Horton 2018), gender (Wang 2017), nationality/geography (Ghani et al 2014, Hong and Pavlou 2017), reputation (Yoganarasimhan 2013, Moreno and Terwisch 2014, Kokkodis and Ipeirotis 2015), and price (Yoganarasimhan 2015). However, to the best of our knowledge, no papers have investigated the effect of factors that reduce the uncertainty buyers have about sellers' ability to satisfy their needs.

In this paper we aim to reduce labor market friction by identifying a new driver of successful matches––workers' job-specific experience. This driver helps buyers reduce the uncertainty of sellers' abilities to satisfy their needs and thus increases the likelihood of a quality match. Because buyers' needs are heterogeneous, workers that are experienced and fit for one job may not be suitable for another job. Although it is natural for jobs of different categories or from different industries to have dissimilar needs (OLMs solve this problem by having job categories), buyers' needs may significantly differ even for jobs of the same category and from the same industry. To capture the nuances of jobs within the same category and industry and thus identify workers' job-specific experience, we design a novel metric based on textual descriptions of job postings.

Labor economists have proposed that job-, or task-specific human capital plays a major role in the labor market (Gibbons and Waldman 2004, 2006). Indeed, subsequent papers have found that workers with job-specific experience tend to perform better (Clement et al 2007, Cook and Mansfield 2014, Ahn et al 2020) and also have increased wages (Gathmann and Schonberg 2010, Stinebrickner et al 2019). However, the job-specific experience used in existing papers are often at the industry level, and thus may be too broad to be of use for operational purposes. In particular, one would not expect an accountant to apply for, or win a job in software development.

Another aspect of job-specific human capital unexplored by labor economists are employers' responses. While previous papers have panel datasets that allow workers to be tracked over time across jobs, it is not observed when a worker applied to another job but failed. If the failed job application is for a job that offers higher wages and future prospects, then previous effects of job-specific human capital on wages are underestimated. OLMs offer the unique opportunity to observe employers' responses and estimate the effect of job-specific human capital on being hired. In this paper we find that indeed employers view greater job-specific experience positively and is more likely to hire experienced workers.

Institutional Background

We are in collaboration with a large North American online labor market. This OLM hosts millions of buyers and sellers and facilitates over one million matches each year. Jobs are posted on this OLM across over 10 industries (e.g., software development, marketing, translation) and over 50 categories (e.g., web development, lead generation, graphics and design). Job matches are facilitated in the following order:

1. Buyer posts a job with a written title and description, selects the category and expertise level of the job, and the expected duration;
2. Sellers apply for the job after finding it from a list of search results based on a self-specified query; the application consists of a written cover letter, price the seller is charging, and the seller's profile and past job performance is visible to the buyer;
3. Buyer selects sellers to conduct an interview, and eventually selects one or more sellers to work on this job and contracts are formed; most hires are made within 48 hours of when the job is posted.

Beyond organic job applications from sellers, buyers may also directly invite specific sellers to apply. It is also possible for buyers to offer private jobs to specific sellers without going through the public application process. After a contract is formed, sellers work for the buyer on the agreed-on project, and the buyer pays sellers based on the agreed-upon price. At the termination of the contract both parties may provide a review and rating of the experience.

Data

Our data comes directly from our industry partner, the North American OLM. In aggregate we combine data from three sources: a table with information about freelancers (i.e., sellers), a table with information about job postings (including which freelancer won the job), and a table with information about job applications (including the charged price). For this paper we analyze job applications that were made for jobs posted between February 1st, 2018 and July 31st, 2018 (inclusive). We filter the jobs to include only those that are open for public applications, are in the Web Development category, and pay an hourly wage (as compared to a fixed price). In total, we have 109,020 job postings and 2,525,585 job applications made across 174,282 freelancers. In order to measure freelancers' job-specific experience we also obtain all job postings of jobs that each freelancer in our sample won from January 1st, 2015 to February 1st, 2018.

Empirical Analysis

In this section we describe how job-specific experience is measured for each freelancer, and provide the empirical specification used to analyze the effect of job-specific experience on freelancers' likelihood of being hired.

Measuring Job-specific Experience

We define Job-specific experience as the amount of experience that a freelancer has with respect to the job that he is applying to. Naturally, the exact components of each job (both the freelancer has completed and is currently applying to) cannot be digitized, but the textual descriptions of each job posting do present an overview of what the buyer expects. Therefore, we can rely on the body of textual descriptions of freelancers' completed jobs to capture his prior experience on the OLM. Finally, to measure job-specific experience we use natural language processing to compute the similarity between freelancers' past body of work with the textual description of the current job he is applying to.

To compute similarities between text data, we must first transform the free text into numerical vectors. This is done via the bag-of-words model, which treats a body of text (document) as a row vector, and occurrences of each word from a dictionary as a specific element in the vector. All documents share the same word dictionary and therefore a word may appear in one document (positive value for the respective element in that row) and not another (zero value for the respective element in that row). After converting the free text into numerical vectors via the bag-of-words model, we take an additional step of processing: term frequency–inverse document frequency (tf-idf) transformation. The tf-idf transformation takes the count of occurrences of each word in each document and multiply it by the logged inverse document frequency of that word (i.e., $\log\left(\#\ total\ documents / \#\ documents\ containing\ the\ word\right)$). This reduces the relative weights of commonly occurring words. After obtaining numerical vectors of each text, we compute the similarity between each freelancer's past body of work and the job he is applying to using cosine similarity, defined as:

$$\cos(\mathbf{A}, \mathbf{B}) = \frac{\mathbf{A} \cdot \mathbf{B}}{||\mathbf{A}||\,||\mathbf{B}||}$$

where **A** is the vector representation of the words in the freelancer's past body of work, and **B** is the vector representation of the words in the description of the job he is applying for. Cosine similarity measures the angular difference between two vectors, with a value of 1 if the two vectors are exactly the same and a value of 0 if the two vectors are completely different (i.e., orthogonal). An advantage of using cosine similarity instead of simply comparing absolute word overlaps or differences is that cosine similarity normalizes the lengths of the documents during comparison. This is important because freelancers have different amounts of total experience (i.e., number of previously completed jobs), and job descriptions can be of different lengths.

Regression Specification

To estimate the effect of job-specific experience, we use the following empirical specification:

$$Win_{ij} = \beta_0 + \beta_1 Price_{ij} + \beta_2 JSE_{ij} + \beta_3 NumApps_j + \boldsymbol{\beta Controls_{ij}} + \varepsilon_{ij} \quad (1)$$

where Win_{ij} equals 1 if freelancer i wins job j, $Price_{ij}$ is the price that freelancer i charges per hour of working on job j, JSE_{ij} is the level of job-specific experience that freelancer i has for job j, $NumApps_j$ is the number of applications that job j received, and $\boldsymbol{Controls_{ij}}$ is a set of freelancer and job control variables. In total we have 32 control variables, including (but not limited to):

- time delay of the freelancer's application
- responsiveness of the freelancer
- past feedback of the freelancer
- past success rate of the freelancer
- expertise tier of the job posting
- whether the freelancer and buyer are based in the same country
- fraction of overlap between the freelancer's and the job's requested skills
- whether the freelancer was invited to apply
- etc.

We use the logit model to estimate the coefficients of the above specification.

Fixed Effects Model

A concern with the above regression specification is the possibility of endogeneity via omitted variable bias. Specifically, there may be other unobserved factors that are correlated with a freelancer's job-specific experience that are not captured by our control variables. To alleviate this endogeneity concern we introduce freelancer-week level fixed effects. The idea is that a freelancer is unlikely to have unobserved changes to his profile within the period of a week. However, during that week freelancers will apply to multiple different jobs, resulting in variations in price, job-specific experience, and the number of applications the job received. Therefore, we have the following empirical specification:

$$Win_{ij} = \beta_0 + \beta_1 Price_{ij} + \beta_2 JSE_{ij} + \beta_3 NumApps_j + \boldsymbol{\beta_4 Controls_{ij}} + \boldsymbol{\beta_5} Fl_i \cdot Week_k + \varepsilon_{ij} \quad (2)$$

Note that many of the freelancer and job control variables removed as they are specific to the freelancer and do not vary over time.

Results

Table 1 below presents the regression estimates from both specifications. As expected, we see that buyers respond negatively to higher prices, and the freelancer's likelihood of winning decreases with increased numbers of applicants (i.e., greater competition). We also find that freelancers with greater job-specific experience are more likely to win a job. Specifically, an increase of 0.1 unit of task-specific experience results in an increase of 16.5% and 10.3% based on the reduced form and fixed effects models, respectively. This is economically significant as there is often a 0.2 unit difference in task-specific experience between more experienced and less experienced freelancers.

Table 1. Drivers of Winning Jobs

	Logit	Logit with FE
Price	-0.0016*** (0.0004)	-0.0145***(0.0015)
Job-specific experience	1.5310*** (0.0517)	0.9770*** (0.0118)
Number of applications	-0.0286*** (0.0003)	-0.0214*** (0.0003)
FE	N	Y

N	2525550	287915

References

~~Ahn, J., Hoitash, R. and Hoitash, U., 2019. "Auditor Task-Specific Expertise: The Case of Fair Value Accounting," *The Accounting Review*, *forthcoming*.~~

~~Chan, J., and Wang, J. 2017. "Hiring Preferences in Online Labor Markets: Evidence of a Female Hiring Bias," *Management Science* (64:7), pp. 2973-2994.~~

~~Clement, M. B., Koonce, L. and Lopez, T. J., 2007. "The Roles of Task-specific Forecasting Experience and Innate Ability in Understanding Analyst Forecasting Performance," *Journal of Accounting and Economics* (44:3), pp. 378-398.~~

~~Cook, J. B. and Mansfield, R. K., 2016. "Task-specific Experience and Task-specific Talent: Decomposing the Productivity of High School Teachers," *Journal of Public Economics* (140), pp. 51-72.~~

~~Gathmann, C. and Schönberg, U., 2010. "How General is Human Capital? A Task-based Approach," *Journal of Labor Economics*, (28:1), pp. 1-49.~~

~~Gibbons, R. and Waldman, M., 2004. "Task-specific Human Capital," *American Economic Review* (94:2), pp. 203-207.~~

~~Gibbons, R. and Waldman, M., 2006. "Enriching a Theory of Wage and Promotion Dynamics Inside Firms," *Journal of Labor Economics* (24:1), pp. 59-107.~~

~~Ghani, E., Kerr, W. R., and Stanton, C. 2014. "Diasporas and Outsourcing: Evidence from oDesk and India," *Management Science* (60:7), pp. 1677-1697.~~

Hong2017a Hong, Y., and Pavlou, P. A. 2017. "On Buyer Selection of Service Providers in Online Outsourcing Platforms for IT Services," *Information Systems Research* (28:3), pp. 547-562.

~~Horton, J. J. 2019. "Buyer Uncertainty About Seller Capacity: Causes, Consequences, and a Partial Solution," *Management Science*, *forthcoming*.~~

~~Kokkodis, M. and Ipeirotis, P. 2015. "Reputation Transferability in Online Labor Markets," *Management Science* (62:6), pp. 1687-1706.~~

Moreno2014 Moreno, A., and Terwiesch, C. 2014. "Doing Business with Strangers: Reputation in Online Service Marketplaces," *Information Systems Research* (25:4), pp. 865-886.

~~Stinebrickner, R., Stinebrickner, T. and Sullivan, P., 2019. "Job Tasks, Time Allocation, and Wages," *Journal of Labor Economics*, (37:2), pp. 399-433.~~

~~Yoganarasimhan, H. 2013. "The Value of Reputation in an Online Freelance Marketplace," *Marketing Science* (32:6), pp. 860-891.~~

~~Yoganarasimhan, H. 2015. "Estimation of Beauty Contest Auctions," *Marketing Science* (35:1), pp. 27-54.~~