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Abstract

A number of papers have examined labor-market discrimination in traditional labor markets and demonstrated that employers have strong tastes over job applicants. However, so far little is known about potential discrimination in online labor markets, where personal information on gender, race, age, education, etc. is not available. Moreover, few studies have discussed another potential discrimination against employers by job applicants. This paper answers this under-investigated question by using data from the world's largest online labor market, Freelancer.com, where all transactions are publicly observable. Estimation results show that applicants have strong preference over the jobs posted by employers from English-speaking developed countries. These employers receive 23.3% higher number of applications from higher-skilled workers, which results in 17.5% lower price through competition. By demonstrating these new empirical findings, this study contributes and bridges the literature on labor-market discrimination and that on online behavior.

JEL classification: J71, J20

Keywords: Discrimination, Online labor market, Job search, Crowdsourcing

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1 Introduction

A number of previous studies consistently find labor-market discrimination, both in developed and developing countries, based on gender, race, education, unemployment status, etc. Those studies including the research that uses fake resume in field experiments demonstrate that potential employers have strong favor against job applicants (Ahmed and Hammarstedt, 2008; Arceo-Gomez and Campos-Vazquez, 2014; Arrow, 1998; Bertrand and Mullainathan, 2004; Donald and Hamermesh, 2006; Hoff and Pandey, 2006; Bertrand, Chugh and Mullainathan, 2005; Carlsson and Rooth, 2007; Fryer and Levitt, 2004; Kaas and Manger, 2012; Krause, Rinne and Zimmermann, 2012). However, so far little is known about the potential discrimination by job applicants against those employers.

As same as employers have specific tastes toward job applicants, it is also possible that job applicants have strong tastes toward potential employers. This issue has not been discussed well in the literature partly because researchers usually cannot observe who applied for a given job. Even in field experimental studies on labor-market discrimination, they use fake resume to examine which job candidates are more likely to win a job. But those studies do not experiment to post fake job openings to analyze who apply for those jobs.

This paper aims to answer whether job applicants also demonstrate strong tastes toward potential employers, by using a unique data set from the world's largest online labor market, Freelancer.com. Online labor markets provide researchers with a rare opportunity to observe all transactions in the market, ranging from what kinds of jobs are posted (job category, budget, required skills, etc.) and detailed characteristics of employers (nationality, reputation, experience, etc.) to who applied for those jobs and each candidate worker's rich information (proposed price, nationality, reputation, etc.).

Such unique data set allows this paper to examine, in particular, whether and how much job applicants care about potential employer's nationality and language. Estimation results demonstrate that job applicants strongly prefer the jobs posted from English-speaking developed countries. Among all the jobs posted by employers from OECD member countries, the jobs from English-speaking countries such as the U.S., the U.K., and Australia will receive 23.3% larger number of applications compared to non-English-speaking countries such as Germany, Italy, Russia, and Japan. Furthermore, those employers from English-speaking developed countries receive job applications from higher quality workers than those from non-English-speaking developed countries.

Analysis also illustrates that, due to a larger number of applications, average proposed prices by workers are significantly lower for the jobs posted from English-speaking developed countries compared to those from non-English-speaking developed countries. In sum, this study highlights the advantage of employers in the U.S., the U.K., and Australia, etc. as workers have strong preference toward the jobs posted from these English-speaking countries.

These findings from the world's largest online labor market contribute to the discrimination literature first by providing new empirical evidence that such tastes also exist in online communities where the information on gender, race, education, etc. is not available. Moreover, this paper bridges the literature on discrimination and that on online behavior, as previous studies mainly focused only on behavior in traditional (offline) labor markets. By using online-review data, recent papers examined the key factors for success in restaurant industry (Anderson and Magruder, 2012; Luca, 2011; Luca and Zervas, 2013; Wang, 2010), hotel industry (Mayzlin, Dover and Chevalier, 2014), and auction market (Melnik and Alm, 2003; LEI, 2011; Cabral and Hortaçsu, 2010; Resnick et al., 2006; Dewan and Hsu, 2004). This study with a large online-market data contributes to this growing literature by shedding new light on workers' tastes in job search.

The rest of the paper is organized as follows. Section 2 provides background information about growing online labor markets and Section 3 shows the summary of data obtained from Freelancer.com website. Section 4 illustrates the empirical strategy, Section 5 highlights the estimation results, and Section 6 concludes.

2 Background

2.1 Overview of online labor markets

Crowdsourcing is a process to find a worker for a specific job from a large group of people (that is "crowd") in an online labor market. This process is different from outsourcing in that outsouring refers to a long-term relationship between known firms while crowdsouring results in a short-term project-based contract between unknown individuals. This online labor market also differs from offline labor markets, as employers and workers do not meet with each other.

Multiple companies offer crowdsourcing services by developing and organizing labor markets in online communities. Among many, Elance (established in 1998), oDesk (2003), and Freelancer.com (2009) are the largest markets with 3.1 million, 2 million, and 7 million members (as of 2013) around the world, respectively. Australia-based Freelancer.com went on public at the Australian Stock Exchange in 2013, and in responce, Elance and oDesk announced their merger and currently provide a combined online market named Upwork.

Such crowdsourcing markets have quickly gained in popularity across the globe. In developing countries, high-skilled workers can now obtain jobs not available in local labor markets but accessible in the online labor markets, expecting higher salary. Those skill-required jobs include, but not limited to, computer programming, software development, and logo designs. Moreover, low-skilled workers have also participated in the online labor markets, as there are many jobs such as data collection and typing that do not require specific skills.

Even in developed countries, the numbers of workers in the online labor market have been increasing, in part because they are looking for the opportunities for an additional salary or for being an independent contractor by quitting a regular job. As a result, online labor markets have become crucial for workers in finding jobs as well as for potential employers in finding skilled workers or inexpensive labor.

2.2 Job matching process in Freelancer.com

Online labor markets have similar characteristics in their market design and mechanism, which I describe below with examples from Freelancer. com, the world's largest crowdsourcing service. First, a potential employer posts a job in this online community. Figure 1 shows project description for a specific job that provides detailed information on the job, required skills to complete the job, and budget range for the job.

Once an employer posts a job, potential workers apply for the job, offering prices and days to complete the job. Figure 2 presents a list of such workers, where all of the first three workers (among many more) proposed \$30 to complete the job in one day. Given a wide variety of proposals from a number of bidders, the employer selects one worker to award the job by taking multiple factors into account. Since this is not an auction, potential employers do not necessarily choose the workers who offered the lowest price or shortest duration for the job. Instead, it is common that employers decide to work with the bidder who proposed relatively high price as long as the employer deems the chosen worker is qualified.

In addition to the proposed price and days in bidders' offers, other information is available to potential employers to help their decision making. In particular, each worker's reputation as well as experience, shown in Figure 3, are useful information for employers to assess the quality of each bidder.

Once an employer selects a worker, then the worker starts the given job. When the worker completes the project, the employer receives an output (such as computer codes, data in Excel file, design and graphic, etc.) and pays for the worker if satisfied with the quality. If the employer is not satisfied with the output, it is possible for the employer to ask the worker for additional changes. Payment transaction is processed through Freelancer.com which makes profit by charging a small proportion of transacted amount to both the employer and the worker.[1]

[1] Freelancer.com also makes revenue by providing premium membership in addition to function-limited, free-of-charge membership.

3 Data

3.1 Summary statistics

This study uses data from Freelancer.com, which organizes the world largest online labor market. All of the information on projects, employers, and bidders (workers) is obtained by web scraping the Freelancer.com's websites in June 2015. Table 1 illustrates the number and proportion of projects by nationality, but the table shows only top ten countries due to a large number of countries. Out of total 5,768 projects, 2,116 (or 36.75%) were posted by U.S. employers. Australia is on the second with 689 projects (11.97%) partly because Freelancer.com is an Australia-based company. Including Canada, the U.K., and Germany, the proportion of the projects posted by employers in developed countries accounts for 62%.

Table 2 demonstrates the breakdown of the same 5,768 projects by job category. The proportion of projects in the category of website, IT, and software is 38%, and that in the category of design, media, and architecture is another 38%, while writing and content occupies 10%. These three top categories together account for as much as 85% mainly because the jobs related to computers, programming, software, design, and writing do not require face-to-face meetings between employers and workers.

By contrast, there are few jobs in Freelancer.com that cannot be completed through online communications, as also shown in Table 2. Only 1.3% of the jobs are categorized as sales and marketing, and only 0.05% are classified as local jobs and services. These projects require that employers meet workers to complete the jobs, and as a result such job openings are usually posted in local offline labor markets, such as advertisement in local newspapers, but not in online markets.

In addition, Table 2 illustrates the average number of bidders for each job category. Overall, there are twenty bidders for each project, but there is a huge difference across job categories. Although the number of posted projects is limited, data entry jobs attract many potential workers with twenty-five bidders on average; this is probably because high skills are not needed for this kind of job, and thus receiving a large number of bidders who want to work for these simple-task projects. In contrast, the average number of bidders is 17.6 for website and IT projects; the number remains lower than the total average in part due to relatively high skills needed for these jobs.

Next, I turn attention to bidders' side who applied for a total of 5,768 projects. Table 3 highlights the top ten countries in terms of the number of bidders. Among a total of 115,150 bidders, India occupies 42.6%, Pakistan 15.5%, and Bangladesh 6.6%. These top three counties combined, all are English-speaking countries in South Asia, account for 64.6% of bidders. However, workers from developed countries are also participating in this online labor market, where the proportions of U.S. and U.K. workers are 4% and 1.5%, respectively.

In sum, while employers (who post jobs) are more likely to be those from developed countries (Table 1), bidders (who apply for the jobs) are more likely to be those from developing countries (Table 2). But this does not imply that employers in developed countries are hiring workers from developing countries. As shown in Table 3, the proportions of Indian and Pakistan workers who won the job through bidding are lower than their proportions in bidding, implying that they have relatively lower chance of winning the jobs. By contrast, U.S. as well as U.K. workers' proportions in winners are higher than those in bidding, suggesting that they are more likely to win the jobs compared to the bidders from developed countries.

Table 4 demonstrates the summary statistics of the data I used in this study. Information from a total of 5,768 projects with a total of 115,150 winners is obtained. Out of 5,768 projects, 75% are posted by employers in developed countries (OECD member countries), while different 75% are posted by employers in English-speaking countries. Each projects has a minimum budget of \$192 and a maximum of \$640 on average. Employers who posted projects, on average, have twenty-one reviews with 4.86 in their reputation (rank, out of 5).

Among a total of 115,150 bidders who applied for those 5,768 projects, only 3.9% are workers from developed countries, and 26% are from English-speaking countries. The average proposed (bidding) price is \$532. On average, bidders have reputation 4.1 (rank, out of 5) and 131 reviews with 4.6 experience (out of 5).

4 Empirical framework

This study examines how job applicants distinguish potential employers, with a specific focus on discrimination regarding nationality and language. In particular, the paper analyzes how the employers' outcomes become different based on whether those employers are from developed countries and on whether they are from English-speaking countries. As a result, the regression equation is represented as follows;

$$y_i = \beta_0 + \beta_1 OECD_i + \beta_2 English_i + \beta_3 OECD_i * English_i + X_i \beta_4 + \epsilon_i, \qquad (1)$$

where i represents potential employer who posts a project.

y_i indicates multiple outcomes, and the first outcome is the number of bidders. To examine how employers' nationality and language affect the number of workers who apply for the job, I use (1) the total number of bidders, (2) the number of bidders from OECD countries, and (3) the number of bidders from English-speaking countries.

The second outcome is (4) the average proposed price by bidders. With this outcome, the study investigates how differently workers charge employers based on employers' background. The third outcome is the quality of bidders. Depending on nationality or language, employers may receive job applications of different quality. This question is answered by using bidders' (5) average reputation (rank), (6) average number of reviews, and (7) average experience.

On the right hand side of the Equation (1), $OECD_i$ and $English_i$ are dummy variables that indicate developed countries and English-speaking countries. The interaction of these dummies are also included in the model. X_i controls for the characteristics of the job posted by potential employer i. Such characteristics include minimum budget and maximum budget to control for the size of a given project. In addition, eleven job categories shown in Table 2 are also included. The econometric model further controls for the quality of the employer, by including the number of reviews as well as the reputation for the employer. All variables for y_i and X_i are in natural logarithm to interpret the coefficient as percentage change.

In the online labor market, employers around the world post their jobs frequently, which makes it difficult for any worker to expect any forthcoming job posts. As a result, it is reasonable to assume that the right-hand-side variables in Equation (1) are exogenous. With this assumption, the model is estimated by OLS.

5 Results

Table 5 represents the main regression results. The first to the third columns use the number of bidders, respectively. The fourth column shows the result with the average proposed price as the outcome variable. The fifth to the seventh columns refer to the results when bidders' average quality was used for the outcome. All specifications further include ten dummies for eleven job categories, but the results are excluded from the table.

For any outcome variable over the seven specifications, the coefficient on $OECD$ is not significant, which implies that whether the employer is from an OECD country does not affect the number of bids, the average proposed price, or bidders' quality.

By contrast, the coefficient on *English* is significant for all of the seven specifications, suggesting that bidders consider the employer's mother tongue as a key factor. Since the outcome is in a natural logarithm form, the results indicate that, compared to potential employers from non-English-speaking countries, those from English-speaking countries receive 23.3% lower total job applications, 27.4% lower job applications from OECD countries, and 13.2% lower job applications from English-speaking countries. Furthermore, the average bidding price will become 12.3% higher, and the average quality of bidders also become lower in terms of rank (reputation), the number of reviews, and experience.

Most interesting finding is the coefficient on the interaction term of $OECD$ and *English*. Compared to the potential employers in non-English-speaking OECD countries (such as

Japan, Italy, etc.), those from English-speaking OECD countries (such as the U.S., the U.K., Australia, etc.) receive, on average, 28.7% more total job applications and 17.5% lower proposed price. Furthermore, the average quality of bidders significantly improve if a job is posted by an employer from English-speaking OECD countries.

These findings suggest that even after controlling for budget and job category as well as employers' characteristics such as reputation and reviews, still job applicants favor the jobs posted by employers in developed country where English is used as an official language.

6 Conclusion

This paper examines how job applicants evaluate potential employers. There exists a rich literature on employment discrimination where potential employers discriminate job applicants based on gender, race, education, etc. However, little is known about the potential discrimination against employers by those job applicants.

This study uses a unique data set from the world' largest online labor market to answer this question. The results show that, even after controlling for job characteristics as well as employers' characteristics, workers still prefer to apply for the jobs posted by an employer in English-speaking developed countries such as the U.S., the U.K., and Australia.

The jobs posted from these countries receive significantly higher number of applications, which results in a significantly lower proposed price through competition. By providing this new empirical evidence, this study sheds new light on labor-market discrimination as well as on the behavior in an online labor market. The direction of this research will be more fruitful in the future.

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Figure 1: Project proposal in Freelancer.com

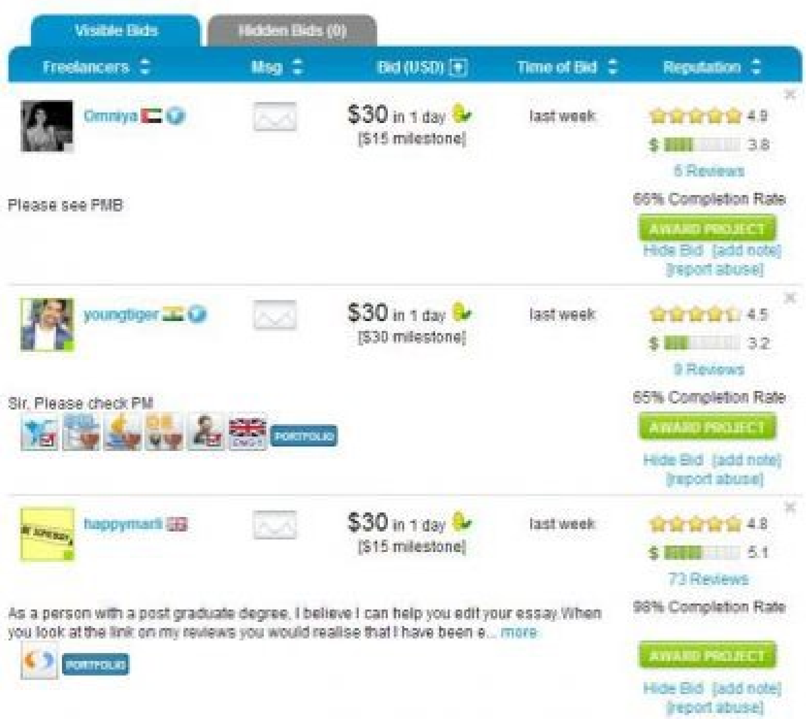

Figure 2: Bidding for a project in Freelancer.com

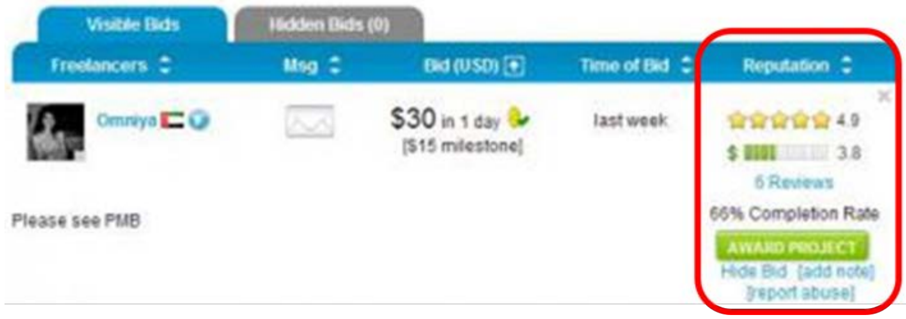

Figure 3: Information on each bidder in Freelancer.com

Table 1: Projects by nationality

Nationality	# of Projects	% of Projects
United States	2,116	36.75
Australia	689	11.97
Canada	362	6.29
United Kingdom	341	5.92
India	297	5.16
Singapore	124	2.15
United Arab Emirates	82	1.42
Israel	80	1.39
Germany	76	1.32
Brazil	69	1.2
Total	5,768	100%

Table 2: Projects by job category

Job category	# of Projects	% of Projects	Ave. # of Bidders
Websites, IT & Software	2,179	37.78	17.56
Design, Media & Architecture	2,219	38.47	23.08
Writing & Content	599	10.38	19.08
Data Entry & Admin	225	3.9	25.08
Mobile Phones & Computing	237	4.11	19.52
Engineering & Science	153	2.65	12.97
Sales & Marketing	76	1.31	11.51
Business, Accounting, Human Resources & Legal	48	0.83	13.48
Translation & Languages	14	0.24	13.78
Product Sourcing & Manufacturing	15	0.26	15.4
Local Jobs & Services	3	0.05	10.67
Total	5,768	100%	19.96

Table 3: Bidders and winners by nationality

Nationality	# of Bidders	% of Bidders	# of Winners	% of Winners
India	49,009	42.56	1,908	33.08
Pakistan	17,804	15.46	823	14.27
Bangladesh	7,599	6.60	380	6.59
United States	4,667	4.05	302	5.24
China	2,824	2.45	152	2.64
Vietnam	2,823	2.45	208	3.61
Romania	2,336	2.03	139	2.41
Ukraine	1,912	1.66	139	2.41
United Kingdom	1,706	1.48	99	1.72
Egypt	1,413	1.23	88	1.53
Total	115,150	100%	5,768	100%

Table 4: Summary statistics

	Variable	Mean	Standard Deviation
(A) Project	OECD country	0.75	0.44
($N = 5,768$)	English-speaking country	0.75	0.43
	Minimum budget	191.85	1219.19
	Maximum budget	639.53	3000.18
	# of Reviews	20.69	54.03
	Rank (out of 5)	4.86	0.70
(B) Bidder	OECD country	3.85	4.74
($N = 115,150$)	English-speaking country	25.73	16.99
	Proposed price	532.25	4982.25
	Rank (out of 5)	4.13	1.71
	# of Reviews	130.91	300.54
	Experience (out of 5)	4.60	2.60

Table 5: Main results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	#bid	#OECD bid	#English bid	Avg. price	Avg. rank	Avg. review	Avg. exp
OECD	-0.0267	0.00145	-0.0579	0.0277	0.0124	0.0949	0.0152
	(-0.59)	(0.03)	(-1.11)	(0.97)	(1.16)	(1.95)	(0.92)
English	-0.233***	-0.274***	-0.132**	0.123***	-0.0464***	-0.205***	-0.125***
	(-5.22)	(-5.69)	(-2.69)	(4.46)	(-4.23)	(-4.21)	(-7.47)
OECD×English	0.287***	0.285***	0.260***	-0.175***	0.0627***	0.296***	0.165***
	(4.97)	(4.72)	(4.01)	(-4.77)	(4.59)	(4.79)	(7.81)
Min budget	-0.00900	-0.0103	-0.0341	0.347***	0.000145	-0.0892***	0.00421
	(-0.49)	(-0.55)	(-1.68)	(29.26)	(0.04)	(-4.96)	(0.68)
Max budget	0.101***	0.0906***	0.121***	0.539***	0.00960*	0.0965***	0.0442***
	(5.80)	(4.94)	(6.16)	(43.53)	(2.41)	(5.19)	(7.13)
Reviews	0.0212**	-0.00858	0.0213*	-0.0156***	0.00540**	-0.0185*	0.00180
	(2.79)	(-1.09)	(2.52)	(-3.29)	(3.11)	(-2.36)	(0.70)
Rank	0.315*	0.209	0.242	-0.108	-0.00522	0.0182	-0.00982
	(2.45)	(1.50)	(1.91)	(-1.08)	(-0.14)	(0.13)	(-0.17)
_cons	1.347***	0.245	1.271***	1.134***	1.302***	4.238***	1.161***
	(5.79)	(0.89)	(5.53)	(6.56)	(17.86)	(15.34)	(10.24)
N	5662	4087	5596	5662	5662	5662	5662

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$