Does Standardized Information in Online Markets Disproportionately Benefit Job Applicants from Less Developed Countries?[1]

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Abstract

We examine trade in services between employers from developed countries (DCs) and workers from less developed countries (LDCs) on an online platform for contract labor. We report evidence that 1) DC employers are less likely to hire LDC compared to DC workers even after controlling for a wide range of observables, 2) workers with standardized and verified work history information are more likely to be hired, and 3) information on verified work history disproportionately benefits LDC contractors. The LDC premium also applies to additional outcomes including wage bids, obtaining an interview, and being shortlisted. In addition, the evidence suggests that informational limits to trade may be addressed through a variety of market design approaches; for instance, an online monitoring tool substitutes for verified work history information.

Keywords: Digital markets, Trade in services, Information standardization

JEL Codes: F16, J20, O33

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1. Introduction

Despite the popular flat-world narrative, evidence demonstrates that trade between countries continues to be affected by geographical, cultural, and other measures of distance. Costs associated with international trade include those that are relatively straightforward to measure such as transportation and tariffs, as well as more indirect ones such as information barriers (e.g. Anderson and Van Wincoop, 2004). Although the precise extent of informational barriers to trade remains unclear, it is hard to dispute that they are substantial (Head and Mayer, 2013). Given the rapid rise of information communication technologies (ICT) over the past quarter century, it is somewhat surprising that distance effects have not diminished more dramatically.

To better understand how improvements in the provision of information affect trade, we study a segment of the economy where advances in ICT do appear to have diminished distance effects: online contract labor markets. Not only do these markets enable distance-insensitive communications between employers and workers, but they also provide enhanced information. We explore how this improved information influences trade between employers in high-wage countries and workers in low-wage countries. Specifically, we examine whether standardized and verified information about job history enabled by online platforms disproportionately benefits contractors from less developed countries (LDCs) relative to those from developed countries (DCs), thus increasing trade in distant services, and find evidence that it does.

Whether enhanced information disproportionately benefits LDC or DC contractors is not obvious. Existing theories and evidence are ambiguous with respect to the effect of information about credentials on hiring decisions. On the one hand, this information might further penalize job applicants at an initial disadvantage (LDC applicants in our data) because employers discount information about individuals in this group, giving a further lead to initially advantaged contractors. Several studies, especially in the literature on labor market discrimination, report this effect (Bertrand and Mullainathan, 2004, Carlsson and Rooth, 2007, Lahey, 2008). On the other hand, there is evidence that information on credentials may disproportionately benefit disadvantaged individuals because, at the margin, information has a higher influence on the employer's perception of the applicant, leading to a larger positive update in beliefs (Figlio, 2005, Heckman et al., 2008, Lang and Manove, 2006, List, 2004, Tilcsik, 2011).[2] We find evidence of the latter.

Trade in services is important, particularly between high- and low-income countries. Head et al. (2009) identify three reasons why import of services from low-wage nations merit special attention:

> *First, the service sector employs about three times as many workers as the goods-producing industries. Second, the service sector contains a relatively large share of highly educated workers. These two facts imply a widening range of workers potentially facing competition from their counterparts in poor countries. [Third], recent technological progress has been much more revolutionary with respect to moving ideas than it has with respect to moving objects.*

North-South exchange dominates the pattern of trade in online contract labor market platforms; employers are predominantly from high-income countries, whereas the majority of contractors are from lower-income countries.[3] Current trends indicate that this is likely to persist. Furthermore, the size of this market is growing rapidly.[4] For example, the quarterly wage bill on oDesk, the largest online contract labor platform at the time of this study,

[2] Altonji and Pierret (2001) offer a theoretical basis for this, suggesting that employers with little information about potential hires may statistically discriminate on the basis of race but that the relationship between race and wages should diminish as employers accumulate more information about worker productivity.

[3] The top contractor source countries on the largest online contract labor platforms, such as oDesk and Elance, include India, the Philippines, Pakistan, Ukraine, the U.S., and Canada; the majority of jobs are posted by companies in the U.S., U.K., Canada, and Australia. oDesk and Elance announced in December 2013 that they planned to merge. The data for this paper was collected in advance of this announcement.

[4] See Agrawal et al. (2015) and Horton (2010) for detailed descriptions of these markets.

increased by approximately 900% over the period 2009-2012 from $10,000,000 to almost $100,000,000.

We base our empirical analysis on 424,308 applications for 14,733 jobs posted on oDesk, the largest and fastest-growing platform for contract labor in the world in January 2012 when we collected these data. We report three main findings. First, applicants from LDCs are only about 60% as likely to be hired by employers from DCs relative to similar applicants from DCs. Despite potential savings from lower wages, prospective employers appear to anticipate problems when hiring from geographically, socially, and culturally distant locations.[5] The magnitude of this difference is striking given the intent of the platform to aggregate and integrate labor markets (Groysberg et al., 2011). This result holds even after we control for many characteristics that employers observe (the ability to observe much of what the employer observes is a particularly research-friendly feature of online labor markets) and for job-level unobserved heterogeneity.

Second, the data indicate a platform-specific work experience benefit; applicants with more platform work experience are more likely to be hired. This finding is consistent with Pallais (2014), who shows that even small amounts of standardized work experience information can dramatically improve employment opportunities as well as wages for contractors.

Third, and most central to the objective of this research, there is an LDC experience premium. Specifically, the benefit from platform work experience information is disproportionately higher for LDC relative to DC applicants. Furthermore, the LDC experience

[5]Our sample includes contractors from 197 countries and territories (which for simplicity we include as separate countries) and employers from 118 countries, 55 of which are high income. As such, countries from all continents and regions, including one contractor living in Antarctica, are represented in our data. However, some countries are much more represented than others. In the sample we analyze, Bangladesh, India, and the Philippines each has over 60,000 contractor-application observations whereas Sub-Saharan African countries are much less represented. For instance, Kenya is the most represented country in this region with slightly more than 4,500 contractor-application observations. In terms of employer countries in our sample, the United States has far more observations than any other country with over 7,500 compared to about 1,200 for the next most represented countries, the U.K. and Australia.

premium is not limited to a narrow categories of tasks (e.g., administrative) but rather applies across a wide range of job. Moreover, the LDC experience premium applies to a variety of outcome measures in addition to our primary hiring outcome. In particular, the wage that individuals bid for a job increases with experience for all contractors, but especially so for those in LDCs. Similarly, the likelihood of being shortlisted and of being invited for an interview both increase with platform work experience and disproportionately so for LDC contractors. Finally, the result seems to be driven by a reduction in information impediments rather than an increase in quality; providing employers access to an online monitoring tool, another form of standardized information about contractor performance, serves as a substitute for platform experience among LDC applicants.

Our results build on prior studies on the effect of online platforms on trade. For example, Lendle et al. (2016) report a 65% smaller distance effect when they compare trade on eBay to total trade. Perhaps most relevant to our focus, they report especially large drops in the distance effect for exporters with PowerSeller status, which requires specific, certified information. Similarly, using data from eBay UK, Elfenbein et al. (2014) estimate a "top-rated seller" certification effect and show it is stronger for categories that have a smaller number of certified sellers, where markets are more competitive, and for sellers with shorter histories on the platform. Hortaçsu et al. (2009) also study trade on eBay, along with a Latin American platform, and report a diminished distance effect, albeit less so than Lendle et al. (2016), who more directly compare online versus offline trade. Cabral and Hortacsu (2010) report evidence of demand sensitivity to information generated on the eBay platform and in particular a significant reduction in sales following the first negative feedback received by a seller. Similarly, Lewis (2011) shows that particular information posted by the seller on eBay Motors, including photos and text, influence prices. In contrast to our study, these focus on trade in goods, which is distinct from services as described in the quote by Head et al. (2009) above. Furthermore, these papers do not focus on the relative effect of information on LDC versus DC sellers.

Our results also build on prior studies that examine the role of other types of information provided through online contract labor markets that enhance trade in services. Mill (2011) examines information from hiring multiple workers from the same LDC country, Pallais (2014) examines information from work experience on the platform and public evaluations, Stanton and Thomas (2015) examine information from agency affiliation, and Gahni et al. (2014) examine information from cultural proximity (Indian diaspora). Our study is most similar to Pallais in that we focus on the effect of contractor work experience on the platform. However, it is distinct in that we focus on the *relative* effect for LDC versus DC contractors and compare the relative effect across job types as well as stages of recruiting (interview, shortlisting, hiring, wage bids); we also examine how the effect interacts with another type of information, which is provided by an online monitoring tool (substitutes). The findings reported in all of these papers are complementary to the results we report here in that they each illustrate a particular channel through which online markets for contract labor enhance trade in services through facilitating the creation and distribution of information. Ours is the only paper that focuses on the relative effect of this information for LDC versus DC contractors.[6]

Overall, we offer three contributions. First, we report what we believe is the first evidence

[6] In terms of the key findings of these important studies, Mill (2011) reports that employers who enjoy a positive experience with a contractor from a particular LDC country have a higher likelihood of hiring another worker from the same country, which the author interprets as consistent with statistical rather than taste-based discrimination. Pallais (2014) reports that a small amount of work experience on the platform as well as publicly posted evaluations generate a surprisingly large effect on subsequent employment, which the author interprets as evidence of a socially inefficient level of hiring. Stanton and Thomas (2015) report that third-party agencies increase the probability that workers are hired and also increase their wages compared to similar workers without an agency affiliation, but that the agency effect diminishes as high-quality non-affiliated workers receive good public feedback scores. The authors interpret their result as suggesting that agencies enhance the efficient allocation of workers to jobs. Ghani et al. (2014) report that DC employers who are members of the Indian diaspora are more likely to hire LDC workers from India. The authors find evidence consistent with both statistical as well as possibly taste-based discrimination. All of these papers utilize data from oDesk with the exception of Mill, who uses data from Freelancer, a similar online market for contract labour.

that, in the context of contract labor, although standardized and verified information benefits everyone, it disproportionately benefits workers from LDCs relative to those from DCs. Second, we show that information-related impediments to trade are sufficiently general that they may be reduced through a variety of market-design approaches (e.g., online monitoring tool substitutes for work history information.) Third, we provide a glimpse inside the black box of ICT, offering an explanation for why it may take time to globalize trade, despite widespread adoption of the internet. Low-cost communications are only a first step in establishing markets that enable rich, standardized, and verified information that influences trading decisions.

We describe our research setting in Section 2, the data in Section 3, and our empirical design in Section 4. We report and interpret our results in Section 5 and offer concluding remarks in Section 6.

2. Research Setting

We conduct our study using data from oDesk, an online platform designed to facilitate employer-contractor matches. The Silicon Valley-based company was founded in 2004 and experienced rapid growth every year since, up to and including the period under study. At the time of this study, the cumulative transaction value exceeded US$900 million, the total number of jobs posted exceeded 2.5 million, and the total number of contractors who were part of the oDesk network was approaching eight million. In terms of the number and value of transactions per year, oDesk was the largest company in its industry, which included other rapidly growing online market makers for contract labor such as Elance (which merged with oDesk in 2013), Guru, and Freelancer. Overall, these online platforms were similar to each other in terms of their purpose, structure, and business model, although there were some differences in areas such as employer monitoring ability, secondary sources of platform revenue, and the types of employer and contractor information provided.

Here is a brief overview of how oDesk works. Employers register on the platform and then post jobs on the site. Contractors register on the platform and then bid for jobs. Bid information includes a proposed fee, cover letter (optional), and profile of the contractor, which lists information such as education, work experience, and location. Employers review bids and have the option to shortlist and interview promising bidders prior to making a decision and hiring a contractor. The employer may decide against hiring any contractor and cancel their job without penalty. Upon completing a job, the employer pays oDesk the pre-specified project fee and rates the performance of the contractor. The contractor also rates the employer. oDesk pays the contractor and records the job in the contractor's job history. We utilize this latter piece of information to measure platform-specific work experience.

Employers classify each job they post as being one of eight types: web development, writing & translation, administrative support, software development, business services, design & multimedia, customer service, and networking & information systems. In addition, the employer provides a description of the job, the skills required to complete it, and the nature of the contract as either hourly or fixed fee. oDesk adds other information to the posting, including the employer's location and their previous activity on oDesk.

Contractors advertise themselves by posting profiles that include information on their education, work history (both on and off the platform), and country of residence. oDesk reports each contractor's profile the contractor's entire oDesk work history, including the amount paid for each job, a description of each job and, for completed jobs, employer feedback. In addition, oDesk offers contractors the option to demonstrate their abilities by taking oDesk-administered tests, although posting the results is optional. Although the majority of contractors work independently, some are associated with agencies that employ staffing managers who handle job applications and take a percentage of the contractor fee.

oDesk's business model is based primarily on transaction fees. Specifically, the platform does not charge employers for posting jobs but does charge employers 10% of the transaction value when a contractor is paid at the end of a job. No additional fees are charged to contractors.

3. Data and Descriptive Statistics

3.1. Dataset Construction

Our data include all job postings and applications on oDesk from the month of January 2012. During this period, employers posted 90,585 jobs. Of these, 45,313 were filled (i.e., contractors were hired); only one contractor was hired in 36,921 of the cases, whereas in the remaining 8,392, multiple hires were made (with a range between 2 and 632). We focus on the cases where a single contractor was hired.[7] The results are robust to including the full set of jobs for which at least one contractor was hired. These results are available in the paper's online appendix Also, we restrict our sample to postings for which at least one applicant was from an LDC, at least one was from a DC, and the job was posted by a DC entity. The final sample includes 14,617 job postings and 420,833 job-application observations.[8]

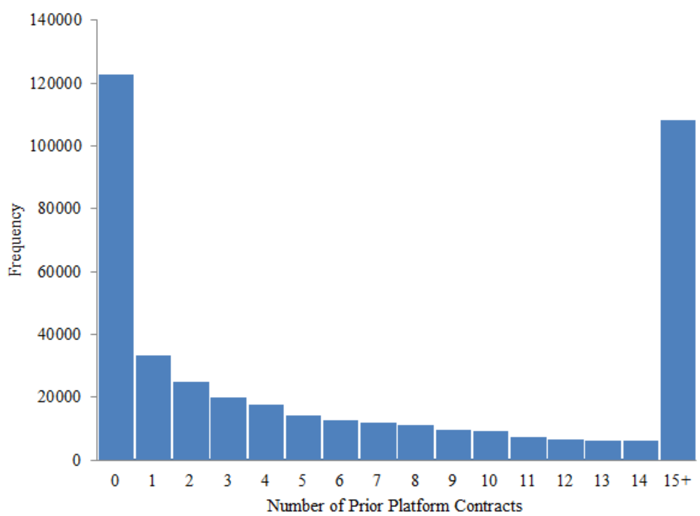
Applicant success (being hired for a given job) is our main outcome variable. We code it as equal to 1 if a contractor is hired and 0 otherwise. Using the World Bank classification scheme (The World Bank Group, 2011), we classify status as LDC by an indicator equal to

[7] Direct experience on the platform and conversations with oDesk personnel revealed that jobs for which multiple people are hired may be posted for a number of different reasons. For example, employers may be running tests or trials in order to then select one single contractor for a subsequent job. The motivations for posting and filling these jobs (and possibly for applying for these jobs) are potentially different than what we normally associate with employer motivation for hiring in ways that would add noise to our data. For these reasons, we limit our sample to jobs for which only one applicant was hired.

[8] In the online appendix, we compare the characteristics of jobs we drop with those we include in our sample. We compare our sample to: (1) the sample of jobs with multiple hires (and both DC and LDC applicants) and (2) the sample of jobs with one hire and either only DC or LDC applicants. Although minor differences exist between the three groups, they look similar along most characteristics, particularly when comparing the sample we use in this paper with the sample of jobs that have only LDC or DC applicants; the differences that do exist between our sample and the multiple hires seem largely due to more hires being made in the latter sample.

1 if a contractor resides in a non-high income country and 0 otherwise. We operationalize platform-specific experience using the number of previous job contracts, with an indicator that equals 1 if contractors have more than the sample median number of prior contracts (4) and 0 otherwise. Figure 1 shows the distribution of online experience in our sample. The distribution is highly skewed, with about 75% of applicants reporting less than 15 previous jobs; a handful of individuals report 100 or more previous tasks completed. The distribution of offline job experience is even more skewed, with the 75th percentile being two jobs, along with a few cases of 50 or more jobs (the maximum is 94). Because of this skewness, we use indicator variables for job experience. Our main findings are robust to more continuous (but still categorical) measures of online experience.

Figure 1: Sample Distribution of Platform Experience



For each observation, we have access to a wealth of information from all applicants' profiles, corresponding to almost everything that market participants observe. As further discussed in Section 4 below, this is a particularly relevant feature of the data because it allows us to control for almost all available information, reducing concerns about omitted variable bias in our regression analysis. We observe contractors' education, work history (both on and off oDesk), test scores, oDesk feedback rating, agency membership, country of residence, oDesk advertised wage, wage bid for a given job, previous jobs held on the platform, whether they have a profile picture, whether they were shortlisted and/or interviewed for the job, and whether or not they have been previously hired by the employer who posted the focal job. We also collect summary information on the application letter; specifically, we measure how original the content of a letter is, relative to an automated form letter. Sending a form letter may reflect scarce interest in a job or poor communication skills. In our analyses below, we find that a higher share of original content does indeed correspond to higher hiring probability. Finally, we have information on whether the application was initiated by the employer or the contractor and job and employer characteristics. We describe all variables and how we constructed them in Table 1.

3.2. Descriptive Statistics

Table 2 reports summary statistics for our sample of contractors (more specifically, contractors-applications), and Table 3 describes our sample of jobs. A large majority of contractors in our sample (364,921, or almost 87%) is from LDCs. Thus, it is not surprising that the average share of applications from LDC contractors for a given job is large (77.7%). However, LDC contractors are only hired for 66.5% of the jobs in our sample.[9] This disproportionately low rate of hiring LDC contractors may be explained by differences in quality between LDC and DC contractors or by differences in the types of jobs they apply for. We address these issues in the regression analyses that follow.

The descriptive statistics reported in the last four columns of Table 2, where we report contractor characteristics, suggest that LDC and DC contractors are similar on many dimensions but quite different in their likelihood of being hired.[10] Some differences beyond the two

[9] A regression on whether a contractor from an LDC is hired for a job on the share of applicants from LDCs for that job, with one observation per job and the constant set at zero, estimates a slope of 0.89, significantly less than 1.

[10] All variables differ significantly across the two groups of contractors, which is not surprising given the large sample sizes. We focus, however, on economic differences and similarities across the two groups.

Table 1: Variable Definitions

Variable	Description
Dependent Variables:	
Applicant Success	Equals 1 if Applicant is Hired for the Job, 0 Otherwise
Log(Wage Bid)	Log of the Bid Applicant makes on an Hourly Wage Job
Log(Fixed Price Bid)	Log of the Bid Applicant makes on a Fixed Price Job
Interviewed	Equals 1 if Applicant is Interviewed for the Job, 0 Otherwise
Shortlisted	Equals 1 if Applicant is Shortlisted for the Job, 0 Otherwise
Key Explanatory Variables:	
Primary:	
LDC	Equals 1 if Applicant is from a LDC, 0 Otherwise
Platform Experience	Equals 1 if Applicant has More Than the Sample Median Number of Prior Jobs on the Platform, 0 Otherwise
Secondary:	
Job Type	5 Types of Jobs with at Least 500 Occurences in Sample: Administration, Marketing, Software Development, Web Development, Writing
Fixed Price	Equals 1 if Contract is Fixed Price, 0 if Contract is Hourly
Employer Experience	Number of Prior Hires Employer has Made on Platform
Contractor Controls:	
Off Platform Work Experience (0/1)	Equals 1 if Applicant has More than the Sample Median Number of Jobs Outside of the Platform, 0 Otherwise
Fraction of Cover Letter that is Original	Fraction of Applicant Cover Letter that Has Not Appeared in Cover Letters Submitted to Other Platform Jobs Applicant has Applied for
Profile Picture	Equals 1 if Applicant has Profile Picture, 0 Otherwise
Platform Rating Score	Applicant's Rating on the Platform
No Platform Rating	Equals 1 if Applicant has No Rating on Platform, 0 Otherwise
Average Platform Test Score	Equals 1 if Applicant's Average Platform Test Score is Above the Sample Median, 0 Otherwise
Number of Platform Tests	Equals 1 if Applicant has Completed More than the Sample Median Number of Platform Tests, 0 Otherwise
Agency Member	Equals 1 if Applicant is a Member of an Employment Agency on Platform, 0 Otherwise
Education	Equals 1 if Applicant has some College Education, 2 if Applicant has a Bachelor's Degree, 3 if Applicant has a Master's Degree, 4 if Applicant has a Doctorate, and 0 Otherwise
Log(Wage Bid)	Log of Applicant Bid on any Contract
Current Offline Employment Status	Equals 1 if Applicant is Currently Employed Outside of Platform, 0 Otherwise
Employer Initiated Application	Equals 1 if Employer Invited Applicant to Apply, 0 Otherwise
Prior Hire	Equals 1 if Applicant has been Previously Hired by Employer of Job Applied to, 0 Otherwise
Job Characteristics:	
Other Job Types	4 Job Types with less than 500 Occurences in Sample: Business Services, Customer Services, Design & Multimedia, and Networks & Information Systems
Number of Interviews	Number of Interviews Performed before Hire
Job Budget	Amount Employer is Willing to Pay a Contractor to Complete the Job, Fixed Price Jobs Only
Final Amount Paid	Total Amount Paid to Hired Contractor, Closed Contracts Only
Number of Applicants	Number of Contractor Applications for Job

Table 2: Contractor Descriptive Statistics

	(1)	(2)	(3)	(4)	(5)	(6)
Sample	Full Sample		DC Contractors		LDC Contractors	
	Mean (SD)	Median	Mean (SD)	Median	Mean (SD)	Median
Applicant Success	0.035	0	0.087	0	0.027	0
	(0.183)		(0.283)		(0.161)	
Contractor-LDC	0.867	1				
	(0.339)					
Number of Prior oDesk Contracts	13.066	4	12.868	3	13.096	4
	(25.612)		(18.261)		(25.181)	
High Platform Experience	0.482	0	0.439	0	0.488	0
	(0.500)		(0.496)		(0.500)	
Off-Platform Work Experience	0.321	0	0.390	0	0.310	0
	(0.467)		(0.488)		(0.463)	
Education	1.196	1	0.916	0	1.237	2
	(1.182)		(1.174)		(1.178)	
Current Non-oDesk Employment Status	0.517	0	0.559	0	0.510	0
	(0.861)		(0.852)		(0.862)	
Average oDesk Test Score	0.499	0	0.682	1	0.473	0
	(0.500)		(0.466)		(0.499)	
Number of oDesk Tests	0.409	0	0.393	0	0.412	0
	(0.492)		(0.489)		(0.492)	
Wage Bid	8.242	5.56	16.871	13.33	7.147	4.44
	(13.418)		(17.764)		(12.338)	
Fixed Price Bid	10.177	7.78	17.736	13.89	8.690	6.67
	(16.286)		(15.872)		(15.950)	
Profile Wage	6.490	4	14.756	12	5.226	3
	(19.797)		(15.040)		(20.130)	
Profile Picture	0.838	1	0.811	1	0.842	1
	(0.369)		(0.391)		(0.365)	
Agency Membership	0.232	0	0.097	0	0.253	0
	(0.422)		(0.296)		(0.435)	
Employer-Initiated Application	0.075	0	0.172	0	0.060	0
	(0.263)		(0.377)		(0.238)	
oDesk Rating Score	3.177	4.7	3.124	5	3.185	4.7
	(2.229)		(2.309)		(2.217)	
No Rating Score	0.695	1	0.662	1	0.700	1
	(0.461)		(0.473)		(0.458)	
Previously Hired by Employer	0.005	0	0.013	0	0.003	0
	(0.067)		(0.115)		(0.056)	
Interviewed	0.111	0	0.188	0	0.099	0
	(0.314)		(0.390)		(0.299)	
Shortlisted	0.038 0		0.050	0	0.036	0
	(0.192)		(0.218)		(0.187)	
Fraction of Cover Letter that is Original	0.301	0.143	0.479	0.5	0.276	0.111
	(0.346)		(0.371)		(0.334)	
Number of Observations	420,833		55,912		364,921	

Notes: This table reports summary statistics at the applicant-job level.

Table 3: Job and Employer Descriptive Statistics

	Mean (SD)	Median
Number of Prior Hires on oDesk	16.346	4
	(46.002)	
Job Type:		
Administrative Services	0.100	0
	(0.301)	
Business Services	0.030	0
	(0.170)	
Customer Services	0.008	0
	(0.091)	
Design & Multimedia	0	0
	(0)	
Networks & Information Systems	0	0
	(0)	
Sales & Marketing	0.089	0
	(0.284)	
Software Development	0.069	0
	(0.254)	
Web Development	0.280	0
	(0.449)	
Writing & Translation	0.193	0
	(0.395)	
Number of Interviews	3.214	2
	(4.857)	
Fixed Price Contract	0.508	1
	(0.500)	
Job Budget	172.882	50
	(947.152)	
Final Amount Paid	463.197	52.22
	(1979.873)	
Number of Applicants	29.005	18
	(44.385)	
Share of LDC Applicants	0.777	0.85
	(0.193)	
Hired LDC Applicant	0.665	1
	(0.472)	
Number of Observations	14,617	

Notes: This table reports characteristics at the employer-job level. Employers indicate how big the budget is for a job only if the job offers a fixed price contract. Only jobs completed during our period of observation have a final amount paid observation.

groups' hiring likelihood are worth noting. LDC contractors are slightly more educated than DC contractors, and they are also more than twice as likely to be members of employment agencies. Contractors from DCs have higher test percentages on average than contractors from LDCs but, given that contractors can delete scores, it is unclear whether this difference is because DC contractors do better on tests or because DC contractors are more likely to delete bad test scores from their profiles. In addition, DC contractors have much higher average advertised wages and wage bids than contractors from LDCs. LDC contractors are less than half as likely as DC contractors to be invited to apply for a job by the employer and much less likely to have been hired by the employer in the past. Finally, LDC contractors write less original cover letters than DC contractors. In summary, although there are some differences between the sample of DC and LDC contractors, they do not appear to reflect clear differences in ability or quality.[11]

The raw data also suggest that experience on the platform, although similar on average between LDC and DC applicants, provides differential benefits in terms of the likelihood of being hired. This likelihood is positively correlated with work experience on oDesk for both LDC and DC contractors. However, in relative terms, LDC contractors benefit more from oDesk experience. Specifically, DC contractors with experience below or equal to the sample median of four previous jobs are about four times more likely to be hired than LDC contractors in the same experience group (0.067 vs. 0.017), whereas the ratio declines to about 3:1 for more experienced applicants (0.114 vs. 0.037). The hiring chances thus increase more than twofold for LDC contractors with above-median experience, as opposed to a 60% increase for DC applicants. Therefore, although a gap remains in hiring chances between LDC and DC workers, having more experience on the platform appears disproportionately

[11] A Blinder-Oaxaca type of decomposition of the likelihood of being hired shows that of the 6.35 percentage points of difference in the likelihood of being hired for DC and LDC applicants (9.08%-2.71%), we can attribute only about 2.6 percentage points to the (observable) characteristics of the applicants.

beneficial to LDC applicants.

These results are consistent with the conjecture that job experience represents a positive signal that increases the likelihood of being hired, where updating on priors concerning quality is relatively stronger for applicants who are at an initial disadvantage. This is akin to a form of statistical discrimination. This applies only for experience on the platform because it is comparable among workers from different origins. It is also a signal of ability on the job because having platform experience also implies having won a contract over competitors for a given job.

The descriptive statistics on wage bids display a similar pattern. The increase in the natural log of wage bids for LDC applicants with and without above-median experience is 0.32, as opposed to 0.24 for DC applicants. The fact that it might take a relatively short period of time to accumulate this experience suggests that the effect is more likely due to the reliability of this standardized information rather than due to the acquisition of skills from the experience. We now proceed to our regression analysis to test the robustness of these basic descriptive findings and our interpretation outlined here.

4. Empirical Strategy

To determine whether standardized information disproportionately benefits job applicants from LDCs in online markets using our data, we need to address a few issues related to the econometric identification.

First, employers may be less likely to hire contractors from LDCs simply because they are of lower quality rather than because of their geographic, social, or cultural distance. Similarly, employers may be more likely to hire contractors with high oDesk experience because they have other qualities valued by employers. However, unlike in labor markets where employers and applicants are able to meet in person and learn more about each other in ways that are unobservable to the researcher, the variables we observe and describe in the previous section represent a large percentage of the information available to employers about applicants.[12] Thus, controlling for these variables in a regression framework considerably allays omitted-variables concerns.

However, we do *not* observe private interactions between applicants and employers (e.g., offline, not mediated/recorded by oDesk). Through these interactions, job posting entities may extract further information on the quality and fit of applicants, potentially related to their origins as well as their experience level or other observables. Some variables in our dataset could be more directly correlated with the likelihood of informal interaction, before or during the job posting and hiring process. For example, in some cases, as mentioned above, employers invite particular contractors to apply for jobs. Also, there are instances where the pool of applicants includes some contractors who worked for the same employer in the past. The analyses reported below are robust to excluding jobs (and all applicants for those jobs) where any of these two indicators is positive for at least one applicant. Another source of information that we do not observe and that is potentially related to the origin and other characteristics of the applicants is the precise content of cover letters that applicants send with their application. If, for example, applicants from LDCs or with lower experience are worse at writing cover letters, then this might indicate lower quality. As mentioned above, we rely on a proxy for the content of the cover letter, as given by the share of original content in the letter.

Second, we account for potential differences across job and employer characteristics by using a regression model that conditions on job-employer characteristics. We model the effect of our covariates on the likelihood of being hired through a conditional fixed-effect logit model (McFadden, 1974), where we group the data by job posting (or employer-job posting) and

[12] We do not control for all observables. For example, we do not control for the specific college attended. However, most of the information that employers observe but that we do not control for is optional and non-verified information.

the alternative set for each job posting includes the applicants to that job. More specifically, we treat each application as a separate observation even though some contractors apply for more than one job in our sample. Of the 420,833 job-application observations, we have 75,972 unique contractor observations.[13] This framework is appropriate in our setting for several reasons. First, employers can only hire from the contractors who apply for their job, and we require employer choice sets to reflect this restriction. Second, it is likely that employers consider all their options when choosing whether or not to hire a contractor so that each hiring decision is conditional on all other applicant characteristics. Third, this model also explicitly assumes that each employer hires the applicant who maximizes her own utility. Fourth, we calculate the likelihood of being hired in this model relative to each job (McFadden, 1974, Cameron and Trivedi, 2009).

More formally, let A_j represent the set of k applicants for job j and let Y_{ij} be an indicator for whether applicant i is hired. Each employer maximizes her utility according to the characteristics of alternatives: $U_{ij} = \alpha + X_i\beta + \epsilon_{ij}$, where X_i is a vector of applicant characteristics, β is a vector of parameters, and ϵ_{ij} is the logit error term (type I extreme value). Therefore, the conditional probability that applicant i is hired out of A_j applicants is:

$$P(Y_i = 1 | \sum_{h \epsilon A_j} Y_h) = \frac{e^{X_i\beta}}{\sum_{h \epsilon A_j} e^{X_h\beta}}, \tag{1}$$

[13]We treat each application as a separate observation even though some contractors apply for more than one job in our sample. We could, in principle, run analyses with individual fixed effects. However, within individuals there is no variation in LDC status, and only for a handful of applicants does the online job experience, our other main variable of interest, move from low to high in the one month of data that we have. In addition, focusing only on those individuals with multiple applications and variation in the experience indicator would censor the sample as the employers would be modeled as choosing an applicant out of a subsample of all applicants for that job. Individual fixed effects would be a way to deal with remaining variation that the employers could observe and the researcher could not; however, given the types of interactions online as explained above, the detailed information we have on each applicant for a job, and the additional robustness tests we describe below, we believe our empirical strategy addresses the possibility of biases from selection or omitted variables. In results not reported in the paper, we verify that our results are robust to controlling for the number of jobs contractors have applied to during the sample period.

where β is a vector of parameters to be estimated through maximum likelihood.[14],[15] Our main regressors of interest are an indicator for whether an applicant is from an LDC and measures of previous job experience.

Third, our estimates may also suffer from selection bias. In particular, more experienced contractors may be better at applying for jobs for which they are likelier to be hired. Because contractor ability to apply for the "right" jobs should not vary with employer characteristics, provided that applicant characteristics do not differ across these employer characteristics, we reject this interpretation of contractor learning below by showing that online experience premiums vary with employer experience on oDesk, whereas applicant characteristics do not.

We also provide analyses with alternative outcome variables as well as additional cuts of the data to corroborate our main findings.

[14]Note that $\sum_{h\epsilon A_j} Y_h = 1$ for each job, because there is only one hire per job in our case. The results are very similar with alternative discrete choice specifications, such as alternative-specific conditional logit as well as mixed logit models with observations grouped at the job-employer level. Alternative-specific conditional logit allow for a separate constant to be estimated for each alternative (the conditional logit model we use here is equivalent to an alternative-specific conditional logit where the constant terms are constrained to be the same). Mixed Logit (or random-coefficients) models allow for coefficients to vary across groups and also overcome a common limit of choice models given by the independence of irrelevant alternatives. The point estimates we obtain from mixed models are almost identical to the conditional logit estimates.

[15]A potential alternative specification would be to use a linear probability model with job-level fixed effects. This would make the interpretation of the estimated coefficients more immediate. However, there would be some important limitations and concerns. First and related to the advantages of a conditional logit framework, a linear probability model would not reflect the choice structure embedded in the hiring problem. In addition, in order for all applicant characteristics to be considered in each individual hiring decision, we would have to make strong assumptions about how these characteristics enter into the employer's choice problem to be able to control for them. One alternative would be to control for all applicant characteristics in each individual decision, but this would be very difficult, particularly with jobs that have many applicants. Finally, in a linear fixed-effect model, there would be an inherent correlation in the error terms due to the fact that for each job posting one and only one hire is possible (and observed). In any event, linear probability models convey very similar estimated marginal effects. The logit coefficient estimates, and in particular the coefficient on the main interaction term of interest, has an immediate interpretation in terms of multiplicative effect.

5. Results

We estimate the existence and size of the LDC penalty, the platform-specific experience benefit, and the LDC experience premium. We examine each in the context of our main outcome measure (likelihood of being hired) as well as three others: attaining an interview, being shortlisted, and wages. We also show that the LDC experience premium is reasonably robust across job types (e.g., administration, web development, writing). We then provide evidence that supports our interpretation that experience is valuable for LDC contractors because of the information it provides employers. Specifically, we report evidence that the information associated with platform-specific experience requires employer investment in learning about the platform; the premium is larger for employers with more hiring experience on the platform. We also report evidence that lowering the cost of monitoring information diminishes the LDC experience premium, implying that these are substitutes.

5.1. Main analyses: Likelihood of being hired for a job

We begin by estimating the LDC penalty (Table 4). The first specification is a pooled logit with standard errors clustered at the job level with no control variables.[16] We then add controls and subsequently employer-job fixed effects. We report both the estimated coefficient and the predictive margins for ease of interpretation. The penalty is large and statistically significant in all specifications. In the uncontrolled logit specification (Columns 1 and 2), the estimated LDC penalty is very large: the probability for an LDC applicant being hired is less than a third that of a DC applicant. When we add controls (Column 4), the coefficient estimate on the LDC indicator increases (margins suggest DC applicants are less than twice as likely to be hired as LDC applicants are), indicating that we can explain part of the LDC penalty by observable quality differences between LDC and DC

[16] We also confirm that our findings are robust to two-way clustering by applicants and jobs using OLS and logit specifications.

applicants.[17] A conditional fixed-effect model (Column 6) estimates a further reduced gap, indicating that there are likely also differences in jobs and employers that affect the likelihood of an employer hiring an applicant from an LDC. These differences can include the quality of matching jobs with applicants, which may be related to the origin of the applicant. Still, even after controlling for alternative-specific covariates and employer-job heterogeneity, we estimate that, all else equal, the average probability that hired is equal to 1 if all applicants are treated as if they are from an LDC is 61% compared to 72% for DC contractors.[18]

As for estimates of the platform-specific experience benefit, in the same three specifications as above (Table 4), we find that, on average, applicants benefit significantly, in terms of the probability of being hired, from work experience on the platform (Column 2). The estimated coefficient on the indicator for platform-specific experience decreases when we add controls (Column 4) but increases slightly when we include job fixed effects (Column 6).

We then move to our primary phenomenon of interest: the LDC experience premium. We add to the set of regressors an interaction term between the LDC and the oDesk experience indicators (Table 5). The estimated coefficients suggest that LDC contractors benefit disproportionately from above-median platform experience compared to DC contractors. In particular, if all applicants are treated as if they are from an LDC, then the mean probability that hired is equal to 1 increases by 13 percentage points when applicants go from having low experience to having high experience. In contrast, if all applicants are treated as if they are from a DC, then this change in experience only increases the probability that hired is equal to 1 by 4 percentage points. To ensure that one particular type of job is not driving our

[17] For simplicity, although we include control variables throughout the remainder of our analyses, we do not report their coefficient estimates in subsequent tables. Also, our findings are robust to including educational levels as separate dummies.

[18] Note that with job fixed effects, the predicted probabilities of being hired are much higher. This is because we are considering the likelihood of being hired for a given job rather than within the sample overall. For instance, although the sample average likelihood that an LDC contractor is hired is 2.7% (see Table 2), the likelihood that any LDC contractor is hired for a given job is 66.5% (see Table 3).

Table 4: LDC Status and Platform Experience

	(1)	(2)	(3)	(4)	(5)	(6)
Model	Logit		Logit		Conditional Logit	
	Estimated Coefficients	Margins	Estimated Coefficients	Margins	Estimated Coefficients	Margins
Platform Experience	0.751***		0.450***		0.464***	
	(0.021)		(0.025)		(0.027)	
LDC	-1.172***		-0.580***		-0.518***	
	(0.022)		(0.025)		(0.026)	
Platform Experience=0		0.023***		0.027***		0.573***
		(0.000)		(0.000)		(0.015)
Platform Experience=1		0.048***		0.041***		0.676***
		(0.001)		(0.001)		(0.013)
LDC=0		0.086***		0.053***		0.719***
		(0.001)		(0.001)		(0.001)
LDC=1		0.029***		0.031***		0.611***
		(0.000)		(0.000)		(0.014)
Off-Platform Work Experience			-0.012		0.076***	
			(0.022)		(0.023)	
Fraction of Cover Letter that is Original			0.810***		0.734***	
			(0.028)		(0.030)	
Profile Picture			0.214***		0.284***	
			(0.028)		(0.030)	
Platform Rating Score			0.128***		0.145***	
			(0.015)		(0.015)	
No Platform Rating			-0.086		-0.235***	
			(0.078)		(0.080)	
Log(Wage Bid)			0.323***		-0.035*	
			(0.015)		(0.019)	
Average Platform Test Score			0.225***		0.262***	
			(0.020)		(0.021)	
Number of Platform Tests			0.067***		0.100***	
			(0.020)		(0.022)	
Agency Member			-0.270***		-0.240***	
			(0.026)		(0.028)	
Education			-0.059***		-0.046***	
			(0.009)		(0.009)	
Current Off-Platform Employment			-0.033		-0.065***	
			(0.021)		(0.022)	
Employer-Initiated Application			1.203***		1.709***	
			(0.038)		(0.055)	
Prior Hire			2.340***		2.183***	
			(0.074)		(0.091)	
Job FEs	No		No		Yes	
Observations	356,480	356,480	356,480	356,480	356,480	356,480
Mean dep var:						
All contractors	0.035	0.035	0.035	0.035	0.035	0.035
DC contractors	0.084	0.084	0.084	0.084	0.084	0.084

Notes: The sample is restricted to jobs posted by employers from DCs and jobs for which one contractor is hired. Standard errors clustered at the job level are reported in parentheses.
$*p < 0.10 **p < 0.05 ***p < 0.01$

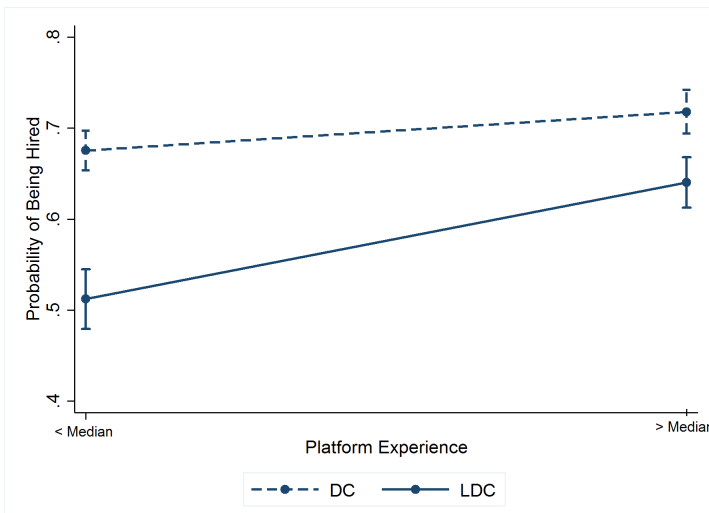
Table 5: Differential Impact of Platform Experience for LDC Contractors

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Full Sample		Estimated Coefficients By Job Type				
	Estimated Coefficient	Margins	Administrative	Web Development	Writing	Software Development	Marketing
Platform Experience	0.209***		0.341**	0.202**	0.127	0.363**	0.227
	(0.044)		(0.155)	(0.096)	(0.084)	(0.175)	(0.172)
LDC	-0.718***		-1.087***	-0.551***	-0.895***	-0.359***	-0.812***
	(0.037)		(0.116)	(0.078)	(0.083)	(0.137)	(0.139)
LDC*Platform Experience	0.346***		0.339**	0.297***	0.478***	-0.057	0.426**
	(0.047)		(0.159)	(0.102)	(0.101)	(0.186)	(0.180)
DC & Low Platform Experience		0.675*** (0.011)					
LDC & Low Platform Experience		0.512*** (0.017)					
DC & High Platform Experience		0.718*** (0.012)					
LDC & High Platform Experience		0.640***					
Observations	356,480	356,480	90,493	87,754	35,201	15,409	44,762
Mean dep var:							
All Contractors	0.035	0.035	0.0145	0.0417	0.0627	0.0563	0.0246
DC Contractors with Low Experience	0.067	0.067	0.031	0.081	0.094	0.085	0.072

Notes: The sample is restricted to jobs posted by employers from DCs and jobs for which one contractor is hired. Standard errors clustered at the job level are reported in parentheses. Controls reported in Table 4 are included in this regression.
$*p < 0.10 **p < 0.05 ***p < 0.01$

main findings, we perform a similar analysis to that reported in Columns 1 and 2 of Table 5 but separately for each job category. We restrict the analysis to job types with at least 500 posted jobs and thus consider the following categories: administrative, web development, writing, software development, and marketing. Our results indicate that the LDC experience premium persists for almost all job categories. One exception is software development; in this case, platform-specific experience benefits all contractors similarly, perhaps because offshoring in software development has been significant over two decades (The World Bank, 2002).

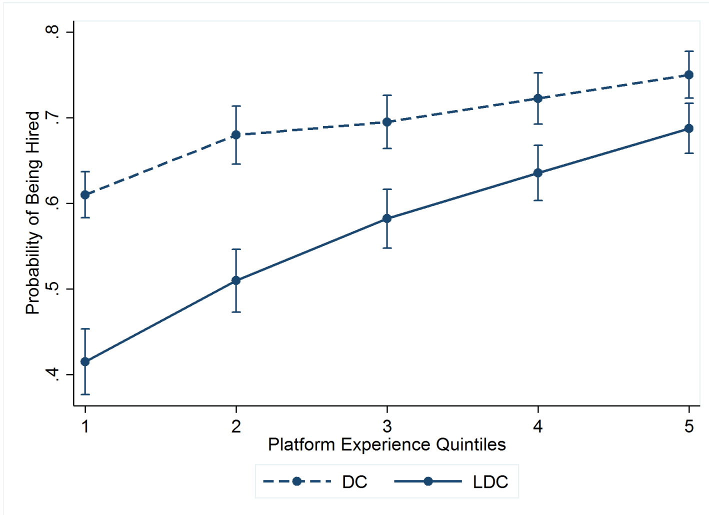
Figure 2: Predictive Margins by Platform Experience & LDC Status



Notes: The probabilities reported in this graph are margins estimated from a conditional logit regression grouped by job postings with controls for contractor characteristics. These controls are offline work experience, originality of cover letters, platform ratings, profile pictures, wage bids, platform test scores and counts, agency membership, education, employer initiation of applications, and prior work with the employer. 95% confidence intervals are included.

We illustrate the coefficients estimated in Table 5 (Column 2) in Figure 2 where we report the average probability of a hiring for LDC and DC contractors by platform experience. The graph demonstrates that LDC contractors are less likely to be hired whether they have low or high platform experience relative to DC contractors. However, LDC contractors benefit more than DC contractors from platform experience. In Figure 3, we plot estimates based on more fine-grained categorizations of the platform experience variable, splitting the sample

Figure 3: Predictive Margins by Platform Experience Quintiles & LDC Status



Notes: The probabilities reported in this graph are margins estimated from a conditional logit regression grouped by job postings with controls for contractor characteristics. These controls are offline work experience, originality of cover letters, platform ratings, profile pictures, wage bids, platform test scores and counts, agency membership, education, employer initiation of applications, and prior work with the employer. 95% confidence intervals are included.

into quintiles of experience level. The main findings persist. The premium is experienced early. Given the average length of a contracted job, the amount of experience required to achieve the premium can be accumulated in a short amount of time.

5.1.1. Alternative Outcome Measures

To the extent that information about experience leads employers to hire disproportionately more contractors who are at an initial disadvantage, then wage bids should increase more with experience for LDC than DC contractors.[19] In Columns 1-4 of Table 6, we report

[19]In general, we expect lower wages for LDCs due to the lower cost of living; however, we do not expect contractor experience to have a differential impact unless information about experience disproportionately affects prior beliefs. A Blinder-Oaxaca decomposition of the log of wage bids reveals that, of the about 0.70 difference in the natural logs of wage bids between DC and LDC employers, only 0.005 (for hourly jobs) and 0.015 (for fixed-price jobs) is attributed to differences in (observable) individual characteristics.

the parameter estimates of this log-linear model:[20]

$$ln(wage_{ij}) = \alpha + \beta_1 LDC_i + \beta_2 Experience_i + \beta_3 LDC_i * Experience_i + \gamma X_{ij} + \eta_j + \epsilon_{ij} \quad (2)$$

where $wage_{ij}$ is the wage bid by contractor i applying for job j. Because bids have a different meaning for hourly and fixed contracts, we perform our analyses separately for these two types of contracts. The other variables are as described in Equation 1 above, and η_j represents fixed effects at the job-employer level (standard errors are clustered at the same level as the fixed effects). An alternative specification that would get closer to giving us causal estimates would include individual fixed effects, exploiting the fact that some individuals apply for multiple jobs over the period of interest. However, there is very little within-individual variation in our main variables; the LDC indicator is invariant across observations for the same individual by construction, and the experience indicators do not vary because of the relatively short time span covered by the data. Therefore, the evidence presented here should be taken as mostly descriptive, though informative.

We estimate significantly lower wage offers (by about exp(-.502)-1=-39%, from Column 2) for inexperienced LDC workers than inexperienced DC workers bidding on hourly wage jobs; however, the increase in wage offers for LDC contractors with experience is about 65% higher than for DC contractors (15.6% increase vs. 9.3%). Similar results hold for fixed price bids, with stronger effects for these jobs. This is consistent with the difference in employers' ability to monitor contractors under the two contract types and suggests that when monitoring is more costly, verifiable information about the applicant is even more valuable. In results not

[20]Comparisons of scale-corrected R-squared and sum of squared residuals (based on a normalized Box-Cox transformation, which is necessary to compare two models where the dependent variable in one of them is a nonlinear transformation of the other) show that the log-linear specification is a significantly better fit than a linear specification for wage. Indeed, the wage level is highly skewed, making linear regressions less reliable. The R-squared from these corrected regressions is about 2.5 times higher both for the hourly and fixed-price contract subsamples, and the chi-squared test for the better fit of the log specification [(N/2)*ln(higher SSR/lower SSR)] is highly significant.

reported here, we limit the sample to bids by the winning contractors. These bids may be better proxies for the equilibrium wage for that particular job, thus they should be more reactive to valuable information. Estimates from the sample of hired contractors are similar to the full sample.

An employer may take two additional steps when considering an applicant for a job: interviewing and shortlisting. In particular, 11% of contractors are interviewed, and those from DCs are much more likely to be interviewed than those from LDCs. On average, about three interviews are performed per job. Shortlisting is less common; only 4.1% of contractors in our sample are shortlisted, and DC applicants are more likely than LDC applicants to be shortlisted (5.9 out of 100 versus 3.9 out of 100). Using an indicator for being interviewed or shortlisted as dependent variables in Equation 1, we estimate the LDC experience premium and report these estimates in columns 5-8 of Table 6. As these estimates demonstrate, our main result concerning the LDC experience premium persists with both upstream measures of success in the recruiting process.

5.2. Interpretation

We interpret our LDC experience premium result as due to standardized information associated with work experience conducted on the platform rather than due to enhanced worker quality from experience. In this section, we provide further evidence consistent with this interpretation. Specifically, we compare the effect of worker platform experience on the likelihood of being hired when worker monitoring is facilitated versus when it is not. We find that this alternate form of *information*, from the online monitoring tool, substitutes for the LDC experience premium. We interpret this result as implying that the LDC experience premium is a result of variance in response to information, not quality.

The platform provides employers with two types of contracts they can use to engage contractors: hourly or fixed fee. The contract type influences the ease of monitoring. Under

Table 6: Differential Impact of Platform Experience for LDC Contractors on Alternative Outcomes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Estimated Coefficients				Estimated Coefficients	Margins	Estimated Coefficients	Margins
Outcome	Log(Hourly Wage Bid)		Log(Fixed Price Bid)		Interviewed		Shortlisted	
Platform Experience	0.170***	0.089***	0.142***	0.114***	0.134***		0.329***	
	(0.013)	(0.009)	(0.011)	(0.009)	(0.040)		(0.055)	
LDC	-0.784***	-0.502***	-0.710***	-0.568***	-0.562***		-0.499***	
	(0.011)	(0.007)	(0.010)	(0.008)	(0.032)		(0.048)	
LDC * Platform Experience	0.066***	0.061***	0.123***	0.089***	0.305***		0.205***	
	(0.012)	(0.009)	(0.011)	(0.010)	(0.042)		(0.058)	
DC & Low Platform Experience						0.618***		0.653***
						(0.008)		(0.011)
LDC & Low Platform Experience						0.486***		0.539***
						(0.012)		(0.018)
DC & High Platform Experience						0.648***		0.719***
						(0.010)		(0.013)
LDC & High Platform Experience						0.589***		0.660***
						(0.011)		(0.015)
Job Fixed Effects	No	Yes	No	Yes				
Observations	221,943	221,943	134,537	134,537	304,768	304,768	132,201	132,201
R-squared	0.214	0.701	0.190	0.469				
Mean dep var:								
All contractors	1.859	1.859	2.099	2.099	0.129	0.129	0.041	0.041
DC contractors with low experience	2.441	2.441	2.593	2.593	0.160	0.160	0.047	0.047

Notes: The sample is restricted to jobs posted by employers from DCs and jobs for which one contractor is hired. Standard errors clustered at the job level are reported in parentheses. Controls reported in Table 4 are included in all regressions. Columns 1-4 report coefficients from OLS regressions. Columns 5-8 report estimates from conditional logit regressions.
$*p < 0.10 **p < 0.05 ***p < 0.01$

hourly contracts, contractors are required to complete their work in a virtual team room where employers are able to monitor their output by way of screen shots and activity monitors in 10-minute increments.[21] The trade-off for this level of monitoring is that employers are obligated to pay contractors for their time regardless of the quality of work, though they can terminate contracts at any time if the work is being poorly done. In contrast, under fixed-fee contracts, contractors are not required to perform their work while logged into the team room, but employers are able to withhold payment if they deem that the output is of poor quality.[22] In other words, employers are protected from poor-quality work through low-cost monitoring in the case of hourly contracts and through optional payment in the case of fixed-fee contracts. Contractors are protected from employer reneging through guaranteed payment in the case of hourly contracts and employer evaluations under both contract regimes.[23]

If the LDC experience premium is due to verified information rather than better quality, as we posit, then it should be greater for jobs done under a fixed-fee contract compared to those done under an hourly contract since the employer is less dependent on this type of information in the latter case due to their ability to monitor. We examine this by splitting the sample by contract type and report our results in Table 7. As expected, the LDC experience premium is significantly higher for jobs conducted under fixed-fee contracts.[24]

This result is interesting for two reasons. First, it provides further insight into recruiting

[21]oDesk takes screenshots of the work of contractors logged into team rooms every 10 minutes so that employers can observe contractors' progress. The platform also keeps track of the number of mouse clicks and movements and generates an activity level measure from this information every 10 minutes.

[22]Employers have the option to not pay the fixed price if they are unsatisfied with the job. However, this happens very rarely, most likely because of reputational concerns (not paying for a job might lead contractors to post bad reviews about a given employer).

[23]Contractors can penalize employers for unfairly withholding payment in fixed-fee jobs by giving them a poor rating, potentially deterring strong applicants from applying to subsequent jobs posted by that employer.

[24]We also run a regression using the full sample, investigate how a job's contract type interacts with LDC status and platform experience, and find results consistent with those reported in Table 7. In particular, we find that platform experience among LDC workers seems to matter significantly more for fixed price contracts than for hourly wage contracts.

Table 7: Differential Impact of Platform Experience by Contract Type

	(1)	(2)	(3)	(4)
Contract Type	Hourly Wage Contract		Fixed Price Contract	
	Estimated Coefficients	Margins	Estimated Coefficients	Margins
Platform Experience	0.229***		0.197***	
	(0.069)		(0.059)	
LDC	-0.730***		-0.713***	
	(0.057)		(0.050)	
LDC * Platform Experience	0.293***		0.412***	
	(0.072)		(0.065)	
LDC=0 & Platform Experience=0		0.500***		0.797***
		(0.018)		(0.012)
LDC=1 & Platform Experience=0		0.339***		0.664***
		(0.021)		(0.021)
LDC=0 & Platform Experience=1		0.553***		0.826***
		(0.021)		(0.012)
LDC=1 & Platform Experience=1		0.453***		0.780***
		(0.021)		(0.015)
Observations	221,943	221,943	134,537	134,537
Mean dep var:				
All contractors	0.028	0.028	0.047	0.047
DC contractors with low experience	0.051	0.051	0.084	0.084

Notes: The sample is restricted to jobs posted by employers from DCs and jobs for which one contractor is hired. Standard errors clustered at the job level are reported in parentheses. Controls reported in Table 4 are included in these regressions. $*p < 0.10 **p < 0.05 ***p < 0.01$

behavior in the online platform context. Tools that lower the cost of monitoring may disproportionately benefit disadvantaged populations; to some extent, they may substitute for other tools that have a similar effect, such as the verified information about prior experience. Second, this result provides further evidence that is consistent with our causal interpretation. We would not expect to see such a difference in the estimated LDC experience premium if it is driven by either better-quality applications or better-quality applicants. Although still not conclusive, the evidence we report here is broadly consistent with our interpretation that the LDC experience premium is due to LDC contractors benefiting disproportionately from standardized platform work experience information.

6. Discussion and Conclusion

Standardized information about work experience conducted on the platform increases the likelihood of being hired for all applicants but does so disproportionately for LDC contractors. Hence, simple but standardized information about even relatively small amounts of platform-specific experience enables companies to potentially reap more benefits from a larger contract labor market. This is especially important when other signals of ability are difficult to interpret, perhaps due to a lack of familiarity with foreign education institutions and employers.

Our findings contribute to a growing literature on labor market globalization. Advances in ICT have contributed to growth in offshoring goods and services. Several papers note the potential productivity gains from service offshoring (e.g., Antràs and Helpman, 2003, Grossman and Rossi-Hansberg, 2008). Antràs et al. (2006) suggest that these productivity gains will be especially pronounced for workers in LDCs. Although we do not test job performance outcomes, our findings have implications for potential information barriers to performance gains from trade in services. Furthermore, these markets have the potential to increase incentives for LDC labor to invest in human capital that is valued by DC employers, thereby increasing the average quality of labor.

Our findings also have implications for research on labor market outcomes for migrants. For example, prior research that considers employer hiring practices in localized DC labor markets where immigrants from LDCs compete with immigrants from DCs and native workers finds significantly lower success rates for LDC immigrants (Ferrer and Riddell, 2008, Oreopoulos, 2011). Oreopoulos (2011) provides evidence that this may be because employers in DCs value work experience acquired in DCs more than similar experience accumulated in LDCs. Dequiedt and Zenou (2013) show that employers statistically discriminate against immigrants because of imperfect information. Our findings reinforce these interpretations and suggest that, even in online labor markets, where technology potentially brings developed and developing economies closer, employers in DCs have difficulties assessing LDC worker quality. Our finding of the relative importance of standardized information for LDC workers might imply that immigrants from LDCs participating in more traditional labor markets in DCs could benefit from carefully constructed and monitored skills certification programs and that employers in DCs could also benefit from certification mechanisms that enhance their ability to screen immigrant applicants.

A further implication of the ability of platforms to facilitate the hiring of distant workers is the potential increase in the returns to outsourcing by lowering transaction costs, thus leading to a more efficient organization of economic activity. This may be of particular importance for small firms that otherwise have difficulty arranging outsourcing agreements in the absence of easily available information. Consistent with the findings in Oster and Millett (2010), these platforms may also change the returns to human capital investments for workers, particularly those in lower income countries, by introducing a pool of relatively high-wage jobs that would otherwise not be available to them. The current growth rate of online markets suggests that they may ultimately affect the geographic allocation of work as well the organization of firms, for example by affecting their optimal size.

The digitization of labor markets, however, comes with challenges for companies and workers. For instance, geographic and cultural differences are likely to affect the ability of workers to collaborate with each other and with their employers (Gaspar and Glaeser, 1998, Lyons, forthcoming). In addition, online markets for labor as well as for other goods and services introduce certain transaction costs due to the inability to meet face-to-face, which can exacerbate information asymmetries (Autor, 2001). One method for addressing these challenges is through the provision of standardized information.

Finally, our findings also resonate with the evidence on discrimination in offline labor (and other) markets that shows that the availability of more information disproportionately improves labor market prospects for disadvantaged populations (Figlio, 2005, Heckman et al., 2008, Lang and Manove, 2006, List, 2004, Tilcsik, 2011). In our setting, it is remarkable how little experience is required to significantly increase contractor success, especially for contractors who are at an initial disadvantage. This suggests an important role for platform-mediated information in global online labor markets.

7. References

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