Geographical Discrimination in Digital Labor Platforms

Hernan Galperin (corresponding author)
Research Associate Professor
University of Southern California
3502 Watt Way, Los Angeles CA 90089-0281
hernan.galperin@usc.edu

Catrihel Greppi
M.A. Economics
Universidad Nacional de La Plata
Centro de Estudios Distributivos y Laborales
La Plata, Argentina (1900)
catrihelgreppi@gmail.com

ABSTRACT

This study seeks to empirically test the narrative of a frictionless global market for digital labor. The empirical strategy is based on the examination of internal data from Nubelo, one of the largest Spanish-language online labor platforms. The results suggest that information-related frictions long observed in traditional labor markets are exacerbated in online platforms, resulting in discrimination based on country of origin. We show that, after controlling for observable workers' characteristics and their job bids, foreign job-seekers are 42 percent less likely to win contracts from Spanish employers, which represent about two-thirds of all employers in the platform. We attribute this result to the activation of social stereotypes that orient employers' hiring decisions, in the absence of verifiable information about the quality of individual workers. We draw implications for platform design and the governance of online labor contracts.

Keywords: DIGITAL LABOR; GEOGRAPHICAL DISCRIMINATION; LATIN

AMERICA; PLATFORM STUDIES.

1. Introduction

There is a familiar narrative about new communication technologies and digital labor. In the pre-Internet days, geography protected many jobs in developed countries from competition by lower-cost workers in the rest of the world. As much as spatial distance discouraged a US or EU resident from getting a haircut in China, it also discouraged organizations from outsourcing back-office operations or software development to other countries. Exponential increases in global telecommunications capacity since the 1980s have made geography virtually irrelevant, creating a globally-contested market for knowledge workers. This has depressed wages and relocated white-collar jobs to developing countries, in a process that closely mirrors the offshoring of blue-collar jobs (Agrawal et al., 2015; Blinder, 2006; Farrell et al., 2005).

From a mainstream development perspective, a similar narrative – but differing in valence – celebrates the rapid diffusion of the Internet and the emergence of online labor platforms as potential drivers of employment and wage growth in developing countries (Raja et al., 2013: Rossotto et al., 2012). The argument is based on a number of stylized facts. First, the majority of employers in online labor platforms are based in high-income countries, while the majority of workers are based in middle and low-income countries (Agrawal et al., 2013; Lehdonvirta and Ernkvist, 2011). This simple fact suggests that workers in developing countries may be able to earn higher (hourly) wages relative to opportunities in local labor markets. Second, online markets dramatically expand the number and range of labor opportunities, facilitating access to employers in higher-wage countries and increasing the likelihood that individual skills will be matched with available jobs. Third, online labor platforms allow employers to

break down large processes into so-called microtasks, enabling individuals or small labor cooperatives to compete directly with offshoring firms that intermediate between employers and workers (Fish and Srinivasan, 2011).

Despite their differences, both narratives share the premise of a frictionless market for digital labor in which workers compete for contracts on a level playing field, regardless of nationality, gender or other characteristics unrelated to individual productivity. In other words, online labor platforms are presumed to be eroding the frictions that result in inferior labor outcomes for women, ethnic minorities and many other groups. By making location irrelevant and allowing employers to screen workers based on verified, productivity-related information, these platforms enable matching between labor demand and supply regardless of physical or cultural distances. This is the narrative of the "flat world" popularized, among many, by Thomas Friedman's best-seller 'The World is Flat: A Brief History of the Twenty-First Century' (Friedman, 2005).

This study seeks to empirically test the narrative of a frictionless global market for digital labor. In particular, we test the hypothesis that cost differentials will induce information labor offshoring to lower-wage countries. Our empirical strategy is based on the examination of internal data from Nubelo, the one of the largest Spanish-language online labor platforms. We obtained records for all transactions in Nubelo over a 44-month period between March 2012 and December 2015. The dataset includes basic demographic characteristics for employers and workers, and extensive platform-specific information about contracted jobs.

Our results suggest that information-related frictions long observed in traditional labor markets are exacerbated in online labor platforms, resulting in a significant penalty for job seekers in developing countries. This penalty works in two ways. First, we show that, after controlling for observable individual characteristics and job bids, workers based in lower-wage countries are 42 percent less likely to win contracts from employers in Spain, the highest-wage country in our sample and where the majority of Nubelo employers are based. Second, we show that Spanish workers are able to command a significant wage premium, of about 16 percent, over similarly-qualified foreign workers. This helps explain why the attrition rate is much higher for workers from developing countries, who are significantly less likely to remain active in Nubelo within 12 months of joining the platform.

We offer two complementary hypotheses for these results. The first relates to the nature of the contracts outsourced through online labor platforms. Most of the job opportunities available in Nubelo (and in similar platforms such as Upwork and Freelancer) require a degree of co-production between buyer and seller. This differs from other platforms, in particular Mechanical Turk, where demand is typically for very small, low-skill tasks that require minimal communication between employer and worker (Irani, 2013). Because employers in Nubelo anticipate higher communication costs when working with foreign contractors, the balance tilts in favor of domestic workers.

However, since the countries served by Nubelo are relatively homogeneous in terms of language and time zone, our second and most relevant hypothesis relates to information asymmetries and uncertainty about worker quality. Because employers are unable to personally screen job seekers, hiring decisions are made on the basis of very limited verifiable

information. In such context, stereotypes that relate country of origin to worker quality provide cognitive shortcuts upon which hiring choices are made. We provide empirical evidence for this mechanism by showing that Spanish employers adjust preferences based on the amount of platform-verified information. In particular, the hiring advantage for domestic workers falls as more information about individual workers is available and employers acquire experience in contracting foreign workers. This suggests employers discriminate due to information uncertainty rather than distaste for hiring workers from other countries.

This study contributes to the emerging literature on the dynamics and socioeconomic impact of digital labor. Our contribution to this literature is threefold. First, we corroborate previous findings about the continued salience of information frictions in a setting where language and other cultural factors are by and large irrelevant. Second, we provide a novel measure to quantify wage differentials between foreign and domestic workers, and explore how wage penalties change when information asymmetries are reduced. Third, we propose a path-dependent mechanism that suggests why, despite very low entry-costs, developing-country workers are less likely to remain active in digital labor markets in the long run.

2. Perspectives on digital labor

The rapid rise of online platforms that facilitate contingent work (often called the "gig economy") has been the subject of significant scholarly attention in recent years. Taking a large-scale perspective, several scholars have examined how market design features embedded in these platforms are exacerbating power imbalances between employers and workers (Kingsley et al., 2015; Fuchs, 2013). A related literature has examined how

contingent work, despite being framed in a discourse of entrepreneurship and family-work balance, may be eroding workers' rights, trapping job seekers from disadvantaged groups in precarious work arrangements (Mann and Graham 2016; Huws, 2015).

We address similar questions from a micro perspective. In particular, our interest lies in the precise mechanisms that determine hiring and wage outcomes in online labor platforms, and thus affect the balance of opportunities and costs associated with digital labor. Our starting point is that the Internet is rapidly changing how labor markets operate. Following Autor (2001), we identify three mechanisms of such change. First, search costs are significantly reduced, potentially improving matching between employers and job seekers. Second, digitization of labor results in more workers (particularly in the service sector) capable of performing their work remotely. Third, online labor makes location much less relevant, freeing both employers and workers from the constraints of geographical proximity.

The third mechanism is of particular relevance to our study. Online labor enables workers in low-wage countries to enter labor markets in higher-wage countries, previously inaccessible due to high communication costs and barriers to migration. Following standard international trade theory, the predicted effect would be to reduce income differences between workers until wages reflect individual productivity rather than geographical proximity to employers (Bhagwati et al, 2004). In the final equilibrium, workers in high-wage countries are made worse off as jobs migrate overseas, driving down wages and reducing employment. At the same time, virtual labor mobility benefits workers in poor countries, expanding market access and improving matching with individual skills.

Several recent studies have examined these arguments in the context of online labor platforms. In general, the findings suggest that information frictions and communication costs reduce potential gains for workers in lower-wage countries. For example, Gefen and Carmel (2008) find that most contracts in an online programming marketplace are awarded to domestic contractors. When jobs are offshored, employers prefer workers from countries with minimal cultural distance (rather than simply lower costs), such as US employers hiring programmers in Canada and Australia. Hong and Pavlou (2014) find that differences in language, time zone, cultural values and levels of economic development negatively affect hiring probabilities in a global platform for IT contracts. Similar results are reported by Lehdonvirta et al. (2014), who also find that the hiring penalty for foreign contractors increases when tasks require knowledge of formal institutions (e.g., legal work) or regular interaction with employers.

Other studies attempt to identify mechanisms that potentially mitigate frictions in online labor markets. For example, Stanton and Thomas (2014) show that being affiliated with an outsourcing firm increases hiring and wages among inexperienced workers, helping them overcome the first-job barrier. The advantage dissipates over time and jobs as more information is available about the quality of individual workers. Ghani et al. (2014) find that ethnic Indian employers based outside India are more likely to hire Indian workers. They attribute the advantage to the familiarity of ethnic Indian employers with information regarding workers' qualifications rather than ethnicity-based preferences. Mill (2011) finds that feedback from previous contracts significantly reduces the effect of geographical location in hiring probabilities. Similarly, Agrawal et al. (2013) find that the benefit of platform-verified information is disproportionately large for contractors from less-developed countries,

which suggests that employers have more difficulty evaluating quality among foreign workers.

In general, these results are consistent with theories of statistical discrimination whereby employers, faced with uncertainty about worker productivity, attribute values based on perceived group averages (Aigner and Cain, 1977; Phelps, 1972). At its core, statistical discrimination is a theory of stereotyping. When hiring workers, employers seek information that helps predict future productivity. If this information is too noisy or simply unavailable, stereotypes provide cognitive shortcuts that help orient hiring choices. Stereotyping has long been studied in the context of traditional labor markets (e.g., Ashenfelter and Card, 1999). However, there are several reasons why it may play an even larger role in online labor platforms.

First, online employers are unable to screen workers in person. While under some circumstances this may reduce hiring biases – most famously when symphony orchestras started implementing "blind" auditions, as shown by Goldin and Rouse (2000) –, it may also trigger stereotyping if reliable signals of worker productivity are unavailable. In Nubelo, as in most online labor platforms, the amount of verified information on workers' profiles (as opposed to voluntarily disclosed) is very limited. In this context, as Pallais (2014) shows, even very small differences in the amount of information available can have a significant effect on future hiring and earnings. Second, given the small monetary value and short-term nature of a typical digital labor contract, it is unlikely that employers will incur in high screening costs (Horton and Chilton, 2010). As a result, faced with several dozen applicants, limited verifiable information and a tight deadline, employers are likely to activate cognitive

shortcuts in hiring decisions. Prior beliefs about the average productivity of workers based on available signals (such as gender and nationality) are likely to become highly salient in such contexts.

3. Data and descriptive results

Nubelo matches employers who post contracts for short-term jobs with workers who bid for these jobs. Job postings typically describe the task required, the job category, the expected date of delivery, and the location of the employer. Employers select workers on the basis of the proposed bid as well as other characteristics that are visible on worker's online profiles. These include name, country of residence, previous work experience in the platform, and a summary feedback score from previous jobs completed. In addition, job seekers can voluntarily include other information such as a CV, a brief description of skills and work experience outside Nubelo, portfolio samples, and a personal picture.

Our dataset includes records for all transactions in Nubelo for a 44-month period between March 2012 and December 2015. They include information on all jobs posted by employers and on all bids placed by workers, both winning and unsuccessful. Unlike other platforms, Nubelo actively discourages employer-worker interaction prior to hiring. Therefore, all the information visible to employers is available in our dataset, reducing concerns about omitted variables in our estimation models. Our units of observation are the bids made by job seekers. As a result, the dataset is restricted to active contractors, by which we refer to those who have submitted at least one bid during the 44-month study period. The full dataset includes 81,497

bids made by 18,356 job seekers for a total of 5,262 jobs posted by 2,517 employers. We note appropriately when partial data subsets are used.

Nubelo primarily serves Spanish-speaking countries. While 63 countries are represented in our dataset, Spain and a few large countries in Latin America account for the majority of job seekers (Table 1). On the other hand, labor demand is largely concentrated in Spain, which accounts for about two-thirds of all employers.

- Table 1 here -

Descriptive results suggest that employers tend to favor job seekers based in Spain. As shown in Figure 1, Spanish workers win a larger-than-expected share of all jobs posted. This difference is magnified when the sample is restricted to Spanish employers: job seekers based in Spain comprise 37 percent of all workers but obtain 65 percent of the contracts originated in Spain.

- Figure 1 here -

On the other hand, when not hiring domestically, Spanish employers hire equally from all other countries in our sample. In other words, the share of contracts awarded to workers across Latin America is proportional to their share of workers in the sample. Figure 2 maps the contracts awarded by Spanish employers to foreign workers. Lines represent country-to-country hiring, with line width proportional to volume. This visual representation

corroborates that much of the contracting in Nubelo takes place between Spain and Latin America, with only limited within-region trade.

- Figure 2 here -

The Nubelo platform supports outsourcing in a broad range of job categories. However as Figure 3 shows, four categories account for the vast majority of transactions: 1) software development, 2) graphic design and multimedia, 3) writing and translation, and 4) IT services. Demand is thus concentrated in relatively high-skill jobs, particularly when compared to microtask platforms such as Mechanical Turk, where lower-skill tasks (such as image identification and data entry) are most common (Ipeirotis, 2010). As expected, the market is tighter in the job categories that require more technical skills, such as software development and IT services. By contrast, competition (as per bids to projects ratio) is particularly intense for contracts in multimedia and graphic design. The intensity of competition and contract prices vary widely across but also within job categories.

- Figure 3 here -

In Nubelo, employers find two categories of information in workers' online profiles. The first category is information about the number of previous contracts obtained, along with the average feedback score received by the worker in these contracts. This information is generated automatically by the platform, and therefore cannot be manipulated by either party. Figure 4 shows the distribution of feedback scores, which is highly skewed towards the

maximum of 5 (\bar{x} =4.73, SD=0.57). This distribution is consistent with previous studies that find feedback scores in online marketplaces to be highly inflated.¹

- Figure 4 here -

It is important to recall that feedback scores are conditional on having obtained at least one contract in Nubelo. As Figure 5 shows, most active workers (i.e., those who have submitted at least one bid during the study period) have never won a contract. At the same time, a small number of successful workers concentrate much of the job volume. This results in a superstartype distribution which is self-reinforcing, given that, as shown below, both work experience and feedback scores are significant predictors of hiring.

- Figure 5 here -

The second category of information available to employers is information voluntarily disclosed by workers. Nubelo encourages job seekers to complete an online profile with details about previous work experience, skills and training, a sample portfolio, and a personal picture. The platform computes the degree to which workers have completed their online profiles by assigning a certain percentage value to different data categories.² As shown in Figure 6, the average worker profile is 80 percent complete. We use this threshold to examine the effect of voluntarily disclosing more (or less) information in our probability models in Section 4.

- Figure 6 here -

Figure 7 shows the distribution of worker activity in Nubelo, measured by the number of bids submitted per job seeker during our study period. While the sample average is 72 bids, the distribution is highly skewed to the left, with a median value of just 15 bids per worker.

- Figure 7 here -

Finally, the evidence reveals high attrition rates, with most job seekers dropping out (or remaining inactive) within the first three months of joining the platform. In fact, about 40% drop out within the first month. This is partly to be expected given the small probability of obtaining a contract for workers without validated work experience and feedback (as discussed in Section 4). However, there are significant differences in attrition rates for Spanish and non-Spanish workers. Workers are most active during their first 3 months after joining Nubelo, as shown in Figure 8. After 3 months, activity levels drop sharply for both groups. However, Spanish workers are more likely to remain active beyond the first trimester, with the domestic to foreign ratio stabilizing at about 1.5:1. We attribute this difference in attrition rates to the cumulative effect of hiring and wage penalties against foreign workers, as described in the next section.

- Figure 8 here -

4. Method and results

Descriptive results suggest a hiring bias in favor of Spanish workers, particularly among Spanish employers. In order to formally test this proposition, we build a linear model that estimates the probability of a worker being hired, conditional on nationality and covariates that capture bid amount, bid timing (in hours after the job is posted), other worker characteristics, and country reputation.³ The vector of worker characteristics includes the number of previous jobs in the platform, a dummy variable for having completed the online profile at or above the sample average of 80 percent, a dummy variable for having positive feedback from previous jobs (i.e., 4 points or more on a 5-point scale), and a dummy variable that indicates whether the job seeker has previously worked with the employer.

Country reputation is measured by the number of times the employer has previously contracted a worker from the same country as the job seeker. Given that most contracts in Nubelo result in positive matches (as shown by high feedback scores), we hypothesize that the more previous hires from a certain country, the more likely the employer will be to hire a worker from that country. Finally, given the variance in the intensity of competition and the value of contracts across jobs, the model includes a jobs fixed-effects term which captures both observed and unobservable differences across jobs.

We restrict the sample to job postings from Spanish employers, for a number of reasons. First, as noted, jobs originating in Spain represent the large majority of postings in Nubelo. Second, our main interest lies in labor offshoring from high-income to lower-income countries. With a GNI per capita of \$28,520 in 2015 (in current US Dollars), Spain's average income is about twice that of Argentina, the second largest employer. Further, during our study period Argentine employers were prevented from hiring outside Argentina (due to government-imposed limits to international payments), which eliminates variance in our main variable of interest. Mexico, the third largest employer with about 8 percent of jobs posted, has a GNI per capita of less than a third of Spain's. Further, given our interest in comparing

outcomes for domestic and foreign workers, we further restrict the sample to job postings that received at least one bid from a Spanish job seeker and one from a non-Spanish (i.e., foreign) job seeker. Finally, filtering for job posting that did not result in a positive match (i.e., where the employer did not hire), our restricted sample comprises 46,799 bids for 2,500 jobs.

4.1. Hiring penalty

The results from Table 2 corroborate that non-Spanish workers are less likely to be hired by Spanish employers. The full model in column 7 (which controls for bid amount, bid delay, country reputation, previous contracts between employer and worker, and covariates related to individual productivity) shows that foreign nationality reduces the winning odds by 2.2 percentage points. Relative to the average winning odds of 5.3 percent in the full sample, this represents a hiring penalty of about 42 percent.

- Table 2 here -

It is interesting to note how the hiring penalty changes as different covariates are introduced. Column 1 represents the basic estimate which only includes bid amount and worker's nationality. In this model, the magnitude of the penalty is about 3 percentage points, which represents a 58 percent penalty relative to the sample mean. In columns 4 to 7 the control variables are sequentially introduced. The penalty remains essentially unchanged until column 6, when individual reputation (i.e., feedback from previous jobs) is introduced. This strongly suggests that Spanish employers attribute quality to workers based on nationality in

the absence of alternative quality signals. These results are summarized in Figure 9, which graphs how the hiring penalty falls as more worker characteristics are introduced in the probability models.

- Figure 9 here -

4.2. Wage premium

Descriptive statistics also suggest that Spanish employers are willing to pay a wage premium for hiring domestically. In order to quantify this wage premium, we build a linear model that estimates bid amount (in log) conditional on nationality and a vector of worker characteristics.⁴ We then restrict the sample to projects that resulted in a Spanish worker being hired. Hence, our coefficient of interest (γ) indicates the marginal change in the amount of bids submitted by foreign workers to the price of contracts ultimately obtained by Spanish workers. In other words, it quantifies the premium that the employer was willing to pay to hire domestically, relative to alternative bids by similarly-qualified (per observable characteristics) foreign workers.

The results in Table 3 indicate that, when hiring locally, Spanish employers rejected alternative bids by foreign job seekers that were, on average, 14 percent lower (column 6). This translates into a wage premium for Spanish workers of about 16 percent when calculated as a premium over alternative bids.

- Table 3 here -

Next we examine if the wage premium varies when more information about workers is available (Table 4). The hypothesis is that the wage premium will be higher for inexperienced workers, for workers with poor feedback, and for workers with less information on their profiles. In order to test these hypotheses, we replicate the full model (column 6 in Table 3) for subsamples of jobs with the following criteria: in model 1, the sample is restricted to jobs that only received bids from workers without previous contracts; in model 2, the sample is restricted to jobs that only received bids from workers with previous work experience. As in Table 3, we restrict to jobs for which a Spanish worker was hired, but that also received (unsuccessful) bids from foreign workers.

As expected, the wage penalty is larger among job seekers without previous contracts (model 1) with respect to job seekers with validated work experience (model 2). In other words, the less information about individual workers is available, the higher the premium employers are willing to pay to hire domestically. Models 3 and 4 are based on a similar exercise. In this case the comparison is between workers with below-average feedback (model 3) against workers with above-average feedback (model 4). The results indicate that having poor feedback from previous contracts disproportionately affects foreign job seekers. As shown, the penalty in model 3 is about three times larger with respect to the case of workers with positive feedback in model 4. Our hypothesis is that employers interpret poor feedback as a confirmation of their prior beliefs about lower average quality among foreign workers.

Finally, we replicate this exercise for jobs that only received bids from workers with below-average information in their online profile (model 5) against the case of jobs where all bidders had average or above-average information in their profiles (model 6). As shown, the foreign wage penalty is almost identical in both cases. This suggests that employers value non-verified information equally for foreign and domestic workers. In other words, this type of information appears to be discounted by employers, for it does not affect the premium paid to Spanish workers.

- Table 4 here -

5. Conclusions

Online platforms offer a valuable laboratory to understand how discrimination operates in various social realms. In some cases, the research interest lies in understanding the algorithms that determine what information is presented to which platform participants, and the potential consequences of such software-embedded choices (Sandvig et al., 2014). In others, the interest is in how discrimination results from choices by participants in multi-sided platforms, and the platform design choices that either promote or mitigate discrimination. Examples include work on discrimination in short-term property rentals (Edelman and Luca, forthcoming), in peer-to-peer transportation (Ge et al., 2016), and in crowdfunding platforms (Pope and Sydnor, 2011).

This study examines geographical discrimination in a short-term labor platform that connects employers with job seekers. We find that discrimination stems from information frictions that trigger cognitive shortcuts among employers. These cognitive shortcuts are, by definition, stereotypes that associate country of origin with expected worker productivity. As shown, when more information about individual workers is available, employers tend to deactivate stereotypes, thus reducing the hiring and wage penalties faced by foreign job seekers.

Previous studies about online labor platforms have found similar results (Pavlou, 2014; Agrawal et al., 2013; Mill, 2011). The key difference with our study is that, when language, time zone and cultural differences between employers and job seekers are large, it becomes difficult to separate the effect of expectations about higher communication costs from expectations about worker quality. For example, a US-based employer may be less likely to hire (or may demand a lower wage from) a worker in the Philippines simply because of the extra effort and costs involved in communicating with this worker, regardless of expected productivity. In this case, geographical discrimination is driven by cost factors, not social stereotypes.

In our study, these confounding factors are minimized. Language differences between Spain and most of Latin America are negligible.⁵ Differences in cultural values are similarly small, particularly when evaluated in the context of the most common jobs in Nubelo, such as multimedia design and web development, which do not require extensive knowledge of local institutions and norms (as would, for example, accounting or legal services). Time zone differences are potentially more relevant. However, including bid timing as a covariate in the regression models does not affect the main results. We are therefore able to attribute

differences in hiring outcomes to idiosyncratic employer assumptions about the productivity of foreign (vs. local) workers rather than cost-related factors.

More broadly, our results suggest that the flat-world metaphor of a globally contestable market for knowledge workers is inappropriate to describe the dynamics of online labor, for a number of reasons. First, it ignores the fact that most tasks cannot be easily routinized or codified, and the ones that can (such as image recognition and data entry) are increasingly being automated. The limits to the commodification of work suggest that most labor market exchanges (whether offline or online) will continue to depend on human relationships and, as a result, be affected by communication costs and information frictions.

Second, because labor markets will continue to depend on relationships, the identities of the transacting parties will also continue to matter. The flat-world metaphor assumes impersonal exchanges in which race, gender, nationality and other personal characteristics become irrelevant. For better or worse, our results indicate that this is not how digital labor platforms operate. In fact, they suggest that stereotypes may play an even larger role in determining hiring and wage outcomes, particularly when employers lack other means of screening workers. Under such circumstances, they are more likely to infer quality based on country of origin. Since the average employer will be less certain about the distribution of quality among foreign (relative to domestic) job seekers, a hiring penalty results.

A number of platform design and policy implications emerge from our findings. First, platform operators can discourage the display of information unrelated to productivity on worker's profiles, while at the same time implement verification mechanisms to validate

skills and previous work experience. This would not only favor workers in developing countries (who, as shown, are penalized disproportionately when lacking verified experience) but also improve employer-worker matching. Horton (2016) estimates that about half of the job contracts posted in digital labor platforms are never filled.

Second, platforms can implement screening mechanisms that help employers identify and interviews job seekers. As mentioned, Nubelo currently discourages employer-worker interaction before hiring, yet other platforms (such as Upwork) in fact promote personal interviews and direct contract negotiation between parties. Following our results, these mechanisms are likely to deactivate stereotypes in hiring choices, thus favoring foreign job seekers, and more generally promoting diversity in job categories currently associated with specific demographic groups.

Finally, employers can be nudged to hire more diversely by altering the order in which alternative candidates are presented. For example, Nubelo attempts to lower the first-job barrier (and thus discourage worker attrition) by favoring job seekers without previous contracts in the algorithm that determines the display of potential matches to employers. A similar nudge could be applied to favor foreign job seekers, or candidates from specific countries underrepresented in certain job categories. In turn, individual hiring will help build country reputation, which as this and other studies (e.g., Leung, 2012) have shown is an important predictor of overall hiring.

Our findings also point to opportunities for collaboration between digital labor platforms and governments in providing skills training and certification. An interesting example is the partnership between Nubelo, Coursera (an online learning platform) and Colombia's Ministry of Information Technologies, which offers online training and certification in high-demand job categories such as web development and digital marketing. Further, governments may adapt youth employment programs to help online job seekers overcome the first-job barrier. As shown, attrition rates are very high, partly due to the small odds of obtaining contracts for inexperienced job seekers entering online labor markets.

Finally, the question of governance for online labor contracts must be addressed to protect workers from the vulnerabilities associated with digital work. These vulnerabilities are multifaceted, ranging from lack of enforcement of minimum-wage legislation to the boundaries of employment relationships (De Stefano, 2016). As an example, a survey of US-based Mechanical Turk workers found that over half earned less than the federal minimum hourly wage (Hitlin, 2016). This and other questions related to the protection of workers' rights only become more pressing when hiring takes place across national borders. In particular, clear jurisdictional lines must be established to enable the enforcement of existing anti-discrimination laws in hiring and compensation in the context of online labor contracting.

FUNDING

This work was supported by the International Development Research Centre (IDRC-Canada), Project #107601-001.

ENDNOTES

¹ For example, Pallais (2014) finds that 83% of data entry workers in oDesk received a rating of at least 4, while 64% received a maximum rating of 5. Similarly, Stanton and Thomas (2014) find that about 60% of workers in oDesk received a feedback score of 5 in their first job.

² For example, a personal picture adds 10 percent to the completeness of the profile, a description of previous work experience adds 5 percent, a description of skills adds 10 percent, and so forth.

³ More formally, the estimated model is:

 $Hiringij = \alpha ij + \gamma Foreignij + \delta log Priceij + \lambda log Delayij + \eta Country Repij + \beta Z + \sigma j + \varepsilon ij$

where Hiring is the probability of worker's bid i being selected for job posting j, Foreign is a dummy (yes=1) that identifies non-Spanish workers, Price denotes bid amount (in log), Delay is the difference (in hours) between the job posting and the bid submission (in log), CountryRep denotes whether the employer has previously hired from the same country of the worker submitting bid i at the time of job posting j, Z is a vector of worker characteristics that vary over time, σ controls for job fixed effects, and ε is an error term.

⁴ More formally, the estimated model is:

 $Log(Price)ij = \alpha ij + \gamma Foreignij + \lambda log Delayij + \beta Z + \sigma j + \varepsilon ij$

where Price is the bid by worker i for job posting j, Foreign is a dummy (yes=1) that identifies non-Spanish workers, Delay is the difference (in hours) between the job posting and

the bid submission (in log), Z is a vector of worker characteristics that vary over time, σ controls for job fixed effects, and ε is an error term.

⁵ Brazil is not relevant for our study, as Nubelo (and many of its competitors) operate a separate platform for Portuguese speakers.

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TABLE 1

CONTRACTORS, EMPLOYERS AND JOBS POSTED BY COUNTRY

| Country | Workers | % | Employers | % | Jobs posted | % |
|--------------------|---------|--------|-----------|--------|-------------|--------|
| Spain | 6,820 | 37.16 | 1,639 | 65.12 | 3,528 | 67.05 |
| Argentina | 4,045 | 22.04 | 390 | 15.49 | 689 | 13.09 |
| Colombia | 2,144 | 11.68 | 139 | 5.52 | 222 | 4.22 |
| Mexico | 1,326 | 7.22 | 175 | 6.95 | 419 | 7.96 |
| Venezuela | 1,268 | 6.91 | 8 | 0.32 | 13 | 0.25 |
| Chile | 648 | 3.53 | 49 | 1.95 | 147 | 2.79 |
| Peru | 399 | 2.17 | 9 | 0.36 | 17 | 0.32 |
| Uruguay | 239 | 1.30 | 10 | 0.40 | 16 | 0.30 |
| Ecuador | 175 | 0.95 | 9 | 0.36 | 50 | 0.95 |
| Dominican Republic | 144 | 0.78 | 6 | 0.24 | 6 | 0.11 |
| Others | 1,148 | 6.25 | 83 | 3.30 | 155 | 2.95 |
| Total | 18,356 | 100.00 | 2,517 | 100.00 | 5,262 | 100.00 |

 $\mbox{table 2}$ Hiring probabilities (ordinary least squares with fixed effects)

| Dependent Variable: Hiring Probability | | | | | | | | | |
|--|-----------|-----------|-----------|-----------|-----------|-----------|-----------|--|--|
| | 1 | | 3 | 4 | 5 | 6 | 7 | | |
| Foreign Penalty | -0.030*** | -0.030*** | -0.029*** | -0.029*** | -0.028*** | -0.022*** | -0.022*** | | |
| | [0.0021] | [0.0021] | [0.0022] | [0.0021] | [0.0021] | [0.0021] | [0.0020] | | |
| Controls: | | | | | | | | | |
| Bid Amount | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | | |
| Bid Delay | | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | | |
| Country Reputation | | | ✓ | ✓ | ✓ | ✓ | ✓ | | |
| Work Experience | | | | ✓ | ✓ | ✓ | ✓ | | |
| Profile | | | | | ✓ | ✓ | ✓ | | |
| Feedback | | | | | | ✓ | ✓ | | |
| Worked w/Employer | | | | | | | ✓ | | |
| Constant | 0.152*** | 0.168*** | 0.167*** | 0.148*** | 0.128*** | 0.0789*** | 0.0743*** | | |
| | [0.00501] | [0.00535] | [0.00539] | [0.00544] | [0.00569] | [0.00580] | [0.00545] | | |
| N | 46,799 | 46,799 | 46,799 | 46,799 | 46,799 | 46,799 | 46,799 | | |
| R2 | 0.011 | 0.013 | 0.013 | 0.022 | 0.025 | 0.050 | 0.161 | | |
| Jobs | 2,500 | 2,500 | 2,500 | 2,500 | 2,500 | 2,500 | 2,500 | | |
| Mean DV | 0.0530 | 0.0530 | 0.0530 | 0.0530 | 0.0530 | 0.0530 | 0.0530 | | |

Standard errors in brackets.

^{***} p<0.01, ** p<0.05, * p<0.1

 $\label{eq:table 3} \mbox{Wage premium (ols with fixed effects)}$

| Dependent Variable: Log of Bid Amount | | | | | | | |
|---------------------------------------|-----------|-----------|-----------|-----------|-----------|-----------|--|
| | 1 | 2 | 3 | 4 | 5 | 6 | |
| Foreign Penalty | -0.120*** | -0.122*** | -0.124*** | -0.125*** | -0.140*** | -0.141*** | |
| | [0.0123] | [0.0122] | [0.0122] | [0.0123] | [0.0123] | [0.0123] | |
| Controls: | | | | | | | |
| Bid Delay | | ✓ | ✓ | ✓ | ✓ | ✓ | |
| Work Experience | | | ✓ | ✓ | ✓ | ✓ | |
| Profile | | | | ✓ | ✓ | ✓ | |
| Feedback | | | | | ✓ | ✓ | |
| Worked w/Employer | | | | | | ✓ | |
| Constant | 4.738*** | 4.615*** | 4.644*** | 4.660*** | 4.746*** | 4.747*** | |
| | [0.00802] | [0.0146] | [0.0152] | [0.0178] | [0.0190] | [0.0190] | |
| N | 31,516 | 31,516 | 31,516 | 31,516 | 31,516 | 31,516 | |
| R2 | 0.003 | 0.007 | 0.008 | 0.008 | 0.014 | 0.014 | |
| Number of Jobs | 1,626 | 1,626 | 1,626 | 1,626 | 1,626 | 1,626 | |
| Mean DV | 281.0 | 281.0 | 281.0 | 281.0 | 281.0 | 281.0 | |

Standard errors in brackets.

^{***} p<0.01, ** p<0.05, * p<0.1

 $\label{eq:table 4} \mbox{Wage premium (ols with fixed effects)}$

| Dependent Variable: Log of Bid Amount | | | | | | | |
|---------------------------------------|--------------------|--------------|----------|------------|----------------------|-----------|--|
| | Previous contracts | | Feedba | ack score | Profile completeness | | |
| | No | No Yes <4 4+ | | 4+ | < 80% | 80% more | |
| | (1) | (2) | (3) | (4) | (5) | (6) | |
| Foreign Penalty | -0.119*** | -0.0792*** | -0.164** | -0.0518*** | -0.122** | -0.135*** | |
| | [0.0285] | [0.0203] | [0.0655] | [0.0174] | [0.0480] | [0.0156] | |
| Controls: | | | | | | | |
| Bid Delay | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | |
| Profile | ✓ | ✓ | ✓ | ✓ | | | |
| Feedback | ✓ | ✓ | | | ✓ | ✓ | |
| Work Experience | | | ✓ | ✓ | ✓ | ✓ | |
| Worked w/employer | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | |
| Constant | 4.916*** | 4.421*** | 4.856*** | 4.482*** | 4.768*** | 4.737*** | |
| | [0.0413] | [0.0493] | [0.0926] | [0.0257] | [0.0638] | [0.0224] | |
| Observations | 7,463 | 8,831 | 1,790 | 13,089 | 2,877 | 17,124 | |
| R-squared | 0.007 | 0.008 | 0.006 | 0.004 | 0.010 | 0.017 | |
| Number of jobs | 518 | 1,108 | 144 | 1,482 | 321 | 1,306 | |
| Mean of DV | 377.5 | 214.0 | 527.3 | 224.6 | 392.1 | 236.6 | |

Standard errors in brackets

^{***} p<0.01, ** p<0.05, * p<0.1

 $\label{eq:Figure 1} Figure \ 1$ workers and contracts awarded by country of origin

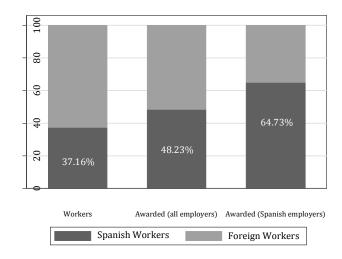


FIGURE 2
BILATERAL CONTRACT ACTIVITY BY COUNTRY

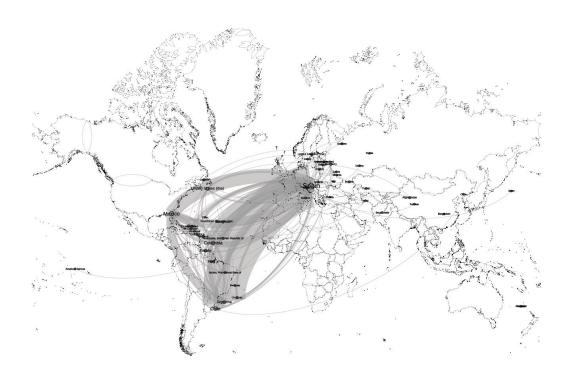
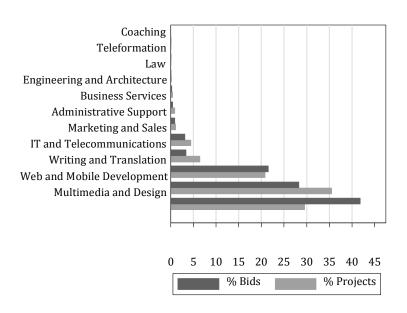


FIGURE 3

JOB POSTINGS AND BIDS BY CATEGORY



 $\label{eq:Figure 4} Figure \, 4$ Distribution of workers' feedback scores (5-point scale)

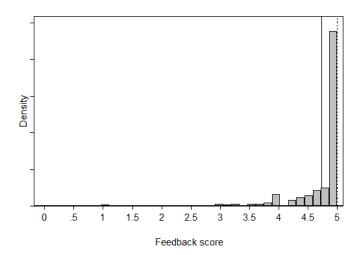
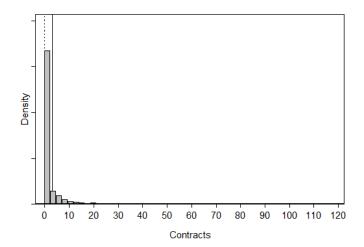
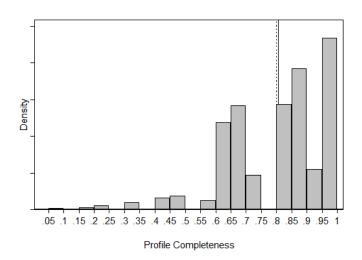


FIGURE 5

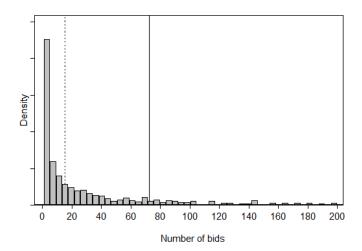
NUMBER OF CONTRACTS OBTAINED BY WORKERS



 $\label{eq:Figure 6} Figure \, 6$ Distribution of online profile completeness



 $\label{eq:Figure 7} Figure \, 7$ Distribution of Bid activity (truncated at 200 bids)



 $\label{eq:Figure 8} Figure \, 8$ Percentage of active workers by number of months after joining

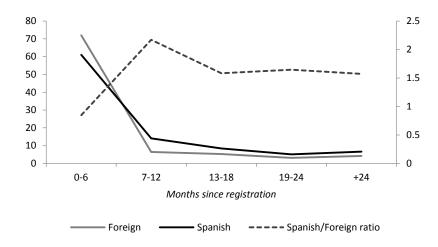
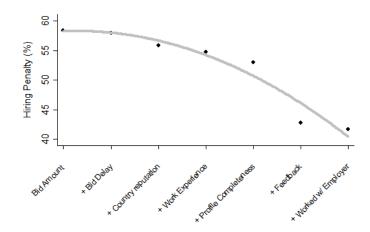


FIGURE 9
HIRING PENALTY IN ALTERNATIVE MODEL SPECIFICATIONS



Source: Author calculations based on Nubelo data. + indicates that the covariate is added to the model.