Landing the First Job:
The Value of Intermediaries in Online Hiring*

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Abstract

This paper studies why outsourcing intermediaries have arisen within online hiring markets. The main finding is that third-party intermediaries provide employers with information that facilitates hiring. They do not increase worker productivity directly or coordinate teamwork. Intermediary affiliation signals that affiliated workers are high-quality compared to independent contractors. This preempts quality revelation on the job and mitigates inefficiently low rates of inexperienced worker hiring. Intermediaries can provide credible certification because affiliated workers share common offline backgrounds. Affiliation is most valuable for highly-skilled workers in developing countries, suggesting that incomplete information impedes the offshore production of skill-intensive tasks.

Keywords: Labor market intermediation, offshoring, incomplete information.

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1 Introduction

The ability to employ workers located anywhere in the world is transforming how employees are both hired and managed—arguably bringing about the next industrial revolution (Blinder, 2006).[1] In his 2001 paper, "Wiring the Labor Market," David Autor predicted that new labor market intermediaries would emerge to enable gains from trade in markets that connect employers with remote workers. One potential intermediation role is to facilitate hiring by providing employers with information about distant workers' productivity. A very different intermediation role involves increasing remote-worker productivity on the job—by performing management tasks such as coordinating teamwork, for example.

Understanding the type of intermediation performed in offshore labor markets exposes both the barriers to trade between employers and remote workers in these markets and also how organizations have arisen to increase market efficiency (Spulber, 1999). If intermediaries exist to provide quality certification that facilitates hiring, then their presence suggests that incomplete information would hamper efficient trade in their absence. If intermediaries manage affiliated workers on the job, this is evidence that efficient use of remote labor in these markets requires complementary inputs or activities.

Intermediaries are now widely observed in markets for remote, offshored work. This paper examines the role of intermediary organizations within oDesk.com, the largest online remote labor market platform. oDesk connects employers with workers for short-term jobs where output is delivered electronically.[2] Around one third of the workers employed on the site are affiliated with one of many small, autonomous intermediaries called outsourcing agencies, which receive a share of affiliates' wages. The remaining two thirds of the employed workers are independent, unaffiliated workers. Outsourcing agencies differ from traditional temporary help supply firms in that, while an employer observes a worker's affiliation status, he contracts directly with the worker rather than with the agency. A typical outsourcing agency consists of between five and ten workers who tend to be located in the same place, who each work in the same skill category, and who often appear to

[1] Blinder and Krueger (2009) estimate that around 25 percent of all jobs in the United States are potentially "offshorable," often made possible by electronic product delivery.

[2] The oDesk platform itself intermediates the worker-employer relationship by providing information and management tools. Employers can observe a large amount of information about potential employees when making hiring decisions, including their work history and feedback scores on prior oDesk jobs. oDesk also provides productivity-enhancing and monitoring software that an employer can use while employing a worker.

belong to shared offline social networks.

This paper makes use of comprehensive administrative data from oDesk on workers' wages and job outcomes, as well as on firms' hiring decisions and project-management practices, to determine why these intermediaries exist. The answer it provides is that outsourcing agencies act as labor market information brokers. Agency affiliation appears to convey to employers that a worker is of relatively high quality, preempting information revelation that takes place on the job. For all workers with experience on the site, an employer feedback score is public information.[3] The feedback score that becomes public information after the first job substitutes for the information conveyed by affiliation, and is, hence, more informative about worker quality for non-affiliates than for affiliates. The value of the information provided by agency affiliation is, thus, greatest for inexperienced workers. The information provided increases efficiency. By credibly signaling that inexperienced affiliates are high-quality, outsourcing agencies serve to increase the total number of experienced workers in the market.

The empirical approach to distinguishing between different outsourcing agency roles relies on the observation that the information about worker quality that agency affiliation conveys to employers during the hiring process is more valuable when other observable data about worker quality are relatively limited. In contrast, if an agency increases worker productivity on the job directly, this productivity effect is likely to be present throughout agency-affiliated workers' oDesk careers. The analysis, hence, asks how and why the wage premium associated with agency affiliation varies over the course of a worker's career on oDesk, as more information about previous on-the-job performance becomes available to employers. The findings are as follows:

Inexperienced affiliates are more likely to be hired than inexperienced non-affiliates; they also earn initial hourly wages that are 60-percent higher, and this premium cannot be explained by differences in team work on the first job (a setting in which worker coordination is likely to be particularly valuable).

Turning to those workers who are hired for a second job: Non-affiliates' wages converge to the wages earned by agency affiliates. The main reason for wage convergence is that re-employed non-

[3] Worker-level feedback is displayed as a score out of five stars, similar to the feedback score on eBay. The score is the revenue-weighted average of the scores received on each prior oDesk job. This feedback mechanism means that oDesk is a public learning environment (Farber and Gibbons, 1996; Altonji and Pierret, 2001; Lange, 2007)

affiliates' hourly wages on the second job are more responsive to the feedback score received on the first job. Differential wage growth is not associated with: worker attributes that were observable on the first job (such as prior experience); characteristics of the first job (such as first-job duration); and differential changes between affiliates and non-affiliates in the characteristics of the first and second jobs (such as team organization).

The next set of findings provides further evidence that wage convergence can be explained by the fact the feedback received on the first job is more informative for non-affiliates because employers have better information about affiliates' quality prior to their first job. Among inexperienced workers, affiliated workers are better quality— employers report project success more frequently for inexperienced agency-affiliated workers than for inexperienced non-affiliates, and the distribution of affiliate feedback on the first job has a higher mean and smaller variance than the same distribution for non-affiliates. Once feedback scores become observable, non-affiliates are less likely to be rehired for subsequent jobs because low-quality workers are selected out of the market.

A separate analysis of employer decision-making, made possible by the uniquely detailed nature of the data, confirms that agency affiliation is informative to employers only for inexperienced workers. Modeling a hire as an employer's discrete choice from a set of workers shows that employers do not attach a positive value to agency affiliation once a worker has been previously employed on the site. There is, however, an incremental positive value associated with agency affiliation for inexperienced workers, which is of similar magnitude whether the employer is hiring for a team-based or an individual project.

One noteworthy feature of the complete set of findings is that outsourcing agency affiliation is most prevalent and most valuable in skill categories in which it is hardest to assess worker quality prior to hiring and before project completion. Over 56 percent of inexperienced workers who find jobs in Web Programming, a highly-skilled task, are outsourcing agency affiliates, compared to just 24 percent of inexperienced workers in Data Entry. Agency affiliation is also more common among workers located in developing countries, whereas the majority of employers on the site are located in the United States. It is likely that employers' ability to assess the quality of inexperienced workers from observable worker attributes, such as the educational establishments attended, is especially limited for foreign workers.

While agency affiliation appears informative only for inexperienced workers, it has important consequences for the overall prevalence of affiliated workers in the employed workforce. Affiliates are higher-quality than non-affiliates, on average, but their increased likelihood of being hired for one job dramatically outweighs the difference in their quality and the difference in their future job success after the first hire. As an illustration, affiliates in Web Programming are around three times more likely than non-affiliates to be hired for at least one job. However, for all workers who have been hired at least once for a Web Programming job, affiliates are only twenty percent more likely than non-affiliates to be hired a second time. This means that a disproportionately small share of inexperienced non-affiliates will have their quality revealed. As a result, an inefficiently small number of high-quality non-affiliates will go on to further employment.

This empirical fact resembles an equilibrium outcome of the model described in Tervio (2009), in which inefficiently low numbers of workers are ever hired.[4] Employers create a worker's reputation when hiring an inexperienced worker; but, since employment contracts are short-term, the employer does not capture the full future benefits that accrue to a good reputation.[5] Using experimental evidence from Data Entry projects, Pallais (2010) confirms the presence of this inefficiency in the oDesk setting. The empirical findings presented in this paper suggest that outsourcing agencies successfully mitigate this inefficiency by credibly certifying inexperienced workers' quality, particularly for those in highly-skilled job categories.[6]

There is no evidence to support the hypothesis that outsourcing agencies intermediate production to increase worker productivity on the job. Under this hypothesis, the agency premium should persist over an affiliate's oDesk career. In particular, the agencies' main role does not appear to be coordinating team production for specialized workers (Becker and Murphy, 1992). While affiliates often work in teams with other agency members, wages for agency-affiliated workers are unrelated to whether the worker is operating in a team or on an individual assignment. For the workers hired

[4] Appendix 1 presents a simple theoretical framework, based on Tervio (2009), to illustrate a perfect Bayesian equilibrium of an overlapping generations model in which agencies reduce information incompleteness and serve to increase output in the market. The empirical findings presented in this paper are consistent with the equilibrium predictions of this model.

[5] Revealing worker quality in this setting is analogous to providing employees with general and, hence, transferable skills (Becker, 1962). Any one employer is reluctant to invest in these worker-specific skills, which the employee can use in other employment settings.

[6] Agency affiliation is, in practice, fixed for the duration of an oDesk career. Interviews with oDesk management in May and June 2010 uncovered the fact that workers wishing to leave an agency must create new worker profiles, losing all previous feedback and work history.

on the site—many of whom work on specialized tasks that could otherwise be performed within the boundaries of the hiring firm—the platform technology successfully allows for arm's-length management.[7]

The data suggest that affiliates are, on average, higher-quality workers, which raises the question of how agencies can screen worker quality. Agencies appear able to screen worker quality and offer affiliation only to high-quality workers due to the shared offline social ties among affiliates of the same agency. As well as being located in the same city and having similar skills, same-agency affiliates have often attended classes together at the same educational institutions. Thus, outsourcing agencies in this setting perform a role that is similar to that played by the experts described in Biglaiser (1993), the certification intermediaries in Lizzeri (1999) and the temporary help supply firms discussed in Autor (2001b), but they do not incur additional screening costs.[8] It is noteworthy that agencies' ability to screen workers relies on the type of social ties that are known to play a role in traditional labor markets, such as referral systems through "Old Boy Networks" (Saloner, 1985). In this way, offline social ties are complementary to online interactions, and are not rendered obsolete by recent developments in communications technology.

While affiliates of the same agency share social ties, it is unlikely that these ties reduce moral hazard on the job by increasing social costs associated with shirking. Employed workers face strong incentives within the oDesk market to refrain from shirking in order to maintain their individual reputations, as summarized in their own feedback score.[9] In addition, the absence of a wage premium for agency affiliates working in teams—a setting where on-the-job monitoring is least costly and, hence, most likely—further undermines the hypothesis that moral hazard concerns drive the equilibrium existence of outsourcing agencies.

The fact that affiliates of the same agency appear to know each other offline also suggests that

[7] Agrawal and Goldfarb (2006) show related evidence that internet adoption directly increases the output of specialized researchers who collaborate across universities (without requiring further intermediation).

[8] In addition, and unlike in Spence (1973), the structure of these intermediaries does not require costly self-selection in order for the signal to be credible since the ability for an agency to screen a given worker appears to depend on the worker being in a pre-existing network. A worker chooses to join an agency and pay a fraction of his wages to the agency because it increases his probability of being hired in the market.

[9] Consistent with the fact that feedback on the first job is strongly positively correlated with the probability of being rehired, and with the hourly wages on the second job, feedback scores are the single most important factor associated with ongoing employment success on the site. Since the interests of individual affiliates and the agency are fully aligned at all stages of an affiliate's career, the role of social ties among members of these organizations differs from the role played by social ties in the rotating savings and credit associations (Roscas) studied in Besley et al. (1993).

the size of any one agency is limited by the boundaries of existing social networks. Furthermore, the reason that agencies are prevalent in the market—inefficiently low levels of hiring of inexperienced workers due to incomplete information about quality—also implies that there are barriers to the entry of new agencies. To start a successful agency on oDesk, a high-quality unaffiliated worker has to be fortunate enough to be hired for at least one job in order to have his quality revealed. Only then can he share his reputation among the high-quality members of his offline network when they join the new agency.

This study of the role played by these intermediaries provides the first empirical evidence that incomplete information constitutes a barrier to efficient trade in offshoring markets, particularly in online services. The findings also imply that other mechanisms that reduce incomplete information are likely to increase transactions' value and, thereby, increase efficiency in these markets. While online intermediaries provide employers with information about worker quality that facilitates hiring and increases total output on the site, their organizational structure indicates that there are constraints on the extent to which agencies can grow to accommodate employer demand. Incomplete information about supplier quality—particularly about high-skilled worker quality—is, hence, likely to limit the rate at which the jobs that are technically offshorable, as defined by Blinder and Krueger (2009), are moved offshore.

The rest of the paper proceeds as follows: Section 2 describes the oDesk marketplace and the data used in the paper. It also provides summary statistics about outsourcing agencies and workers on the site, and then motivates our empirical approach. Section 3 presents the empirical analysis of worker-level wages. Section 4 examines outcomes on worker-level output measures and the probabilities of subsequent jobs. Section 5 examines employers' hiring decisions. Section 6 concludes.

2 The oDesk.com Marketplace

2.1 Background

A firm that wants to hire a remote worker can create an account on oDesk.com, post a project description, and view the profiles of potential job applicants located around the world.[10] A variety of job tasks are posted on the site, falling into three broad categories: First, there are tasks requiring specialized skills where the output may be verified only at the end of a project, such as in Software Development and Web Programming. Second, there is highly-skilled but easy-to-monitor work such as Website Design, where output quality can be observed during the project. Finally, there are low-skilled and easy-to-monitor tasks such as Data Entry. Employers post the expected duration of work in their job advertisements.

Employers observe a large amount of information about each applicant from a detailed profile, including education and work experience outside oDesk. For experienced oDesk workers, a verifiable job history is available, including a revenue-weighted feedback score, out of five, from past jobs.[11] Figure 1 provides a sample worker profile containing the information employers observe when first evaluating a job applicant. Evgeny M., a very successful worker, is located in Omsk, Russia and is a programming specialist. From 2007, when he joined oDesk, to 2010, he earned over $400,000 in wages. The top right corner of Figure 1 shows that Evgeny has excellent feedback from past jobs—scoring 5 out of 5.

On the bottom right-hand side of Evgeny's profile, employers can observe that he is affiliated, along with 17 other workers, with the outsourcing agency *qcode*. Employers can also see the agency-level feedback score of 4.95 out of 5—this is the revenue-weighted feedback score for all jobs started by any worker who was ever affiliated with the agency. In fact, Evgeny heads *qcode*, which means that he collects a share of the revenues generated by other members of the agency. The share paid to the agency is determined by the worker and the agency in question, and varies across agencies.[12]

Many features of *qcode*'s organization appear typical of the other outsourcing agencies operating

[10]The data used in the paper do not contain information on whether workers and firms use other internet platforms in addition to oDesk.

[11]Potential employers can also choose to view any detailed feedback left by prior employers. Many potential employers choose to interview a subset of candidates online prior to hiring decisions.

[12]The share of revenue collected by the agency head is not contained in the data that oDesk collects, but oDesk's management reports that agency heads typically take between three and six percent of affiliated workers' wages.

on oDesk. Almost all qcode-affiliated workers are currently located in Omsk, and most attended the same local university. Figure 2 provides a histogram of agency sizes and the average concentration of agency workers in the modal city for each agency. 75 percent of all agency members are in the modal city for their respective agency affiliates. Among agency members who report their school, 65 percent attended the modal school for their agency. Members of the same agency also tend to work in the same narrowly-defined job category. For example, out of 76 job categories, over 80 percent of experienced agency members have had at least one job in the modal job category for their agency.

2.2 Summary statistics for inexperienced workers

During the sample period between August 1, 2008 and December 28, 2009, nearly 125,000 workers signed up with oDesk. The information that oDesk collected about these workers, both before and after their first job on the site, make up the data used in this paper.[13] Ten percent of these new workers were affiliated with an outsourcing agency, but affiliates made up 33 percent of workers who were hired for at least one job. Table 1 presents summary information about the prevalence of agency affiliation among these workers overall; within the three most frequently observed job categories; and then within four frequent worker-countries. Affiliates are particularly prevalent in the Web Programming job category, compared to Data Entry and Web Design, and affiliates in Web Programming are particularly likely to be hired; 45 percent of affiliates in this job category find work, compared to around one in four in the other two job categories. Table 1 also reveals that affiliates are more prevalent in India and Russia than in the Philippines and the United States.

Across all hired workers, non-affiliate workers appear to have higher levels of observable skills than affiliate workers. Hired non-affiliates are: more likely to have better English language skills (87 percent compared to 82 percent); more likely to report having at least an undergraduate degree (40 percent compared to 35 percent); and more likely to have taken at least one of the skills certification tests administered by oDesk (78 percent compared to 59 percent).[14] Despite these

[13]It does not incorporate earlier data because of changes to the database that records agency affiliation. A separate database query contains the subsequent employment histories, up to 9/8/2010, for all the workers that entered the platform between 8/1/2008 and 12/28/2009.

[14]Appendix Table 1 reproduces these summary statistics for all workers who bid for at least one job between 8/01/2008 and 12/28/2009. While hired agency affiliates appear less skilled than hired non-affiliates, affiliates tend to appear more highly-skilled than the average non-affiliate bidder. This suggests that employers use observable

differences, affiliates tend to receive significantly higher hourly wages on their first job, as shown in the final rows of each panel in Table 1. The average hourly wage (in levels) on a first hourly job for non-affiliates is around $4.85, whereas affiliates earn, on average, $8.08.[15] Figure 3 further shows that within most countries other than the United States, the distribution of affiliates' first wages in Web Programming has a higher mean and smaller variance than the distribution of non-affiliates' first wages.

2.3 Framework motivating the empirical approach

Table 1 reveals a puzzling finding in the data: Employers are more likely to hire inexperienced affiliates than inexperienced non-affiliates and pay them higher initial wages, even though inexperienced agency-affiliated workers appear less skilled. There are two additional facts present in the data set that closely mirror the equilibrium of the public-learning model in Tervio (2009), which demonstrates market failure in the discovery of talent. These facts are: 1) For experienced workers, publicly available feedback scores are highly correlated with both wages and the probability that a worker is hired; and 2) Overall, a small proportion of all workers in the data are employed for many jobs, and these workers earn high wages.

In Tervio's model, where the quality of all inexperienced workers is unknown, an inefficiently low number of inexperienced workers are employed in equilibrium because the firm that incurs the cost of talent discovery (analogous to hiring a worker without feedback in the oDesk setting) does not reap the full benefit of a high-quality worker's good reputation that is created on the job. Superstars, however, (analogous to oDesk workers like Evgeny M.) earn high wages and are always employed. In this equilibrium, wages are proportional to expected quality, but the wages of inexperienced workers cannot adjust enough to overcome the inefficiency of incomplete information.

A simple version of Tervio's original model that allows an intermediary agency to capture the benefits associated with talent discovery illustrates how agencies can reduce inefficiencies arising from incomplete information. The first appendix to this paper outlines this simple extension in a discrete-time setting with two worker-quality levels where worker quality is revealed on the job. The

worker characteristics to help distinguish between non-affiliates of different qualities.

[15] There are also payment-per-project, or "fixed-price," contracts on the site. These contracts make up a small percentage of the job postings for highly-skilled tasks. Non-affiliates are more likely than affiliates to have a prior fixed-price job before receiving a first hourly job.

agency head has a comparative advantage in evaluating the ability of a subset of new workers, and, in equilibrium, offers agency affiliation only to the high-quality workers in this subset. The following empirical predictions are consistent with a perfect Bayesian equilibrium of this model, where employed workers earn wages that are positively correlated with their expected marginal product: (1) Affiliates earn higher initial wages; (2) Non-affiliates who receive good feedback (revealing them to be high-quality) have larger subsequent wage increases than agency affiliates with similar feedback scores.

The second of these predictions results from the fact that feedback from employment substitutes for the information conveyed by agency affiliation. There is no rationale for differential wage responses to feedback in a model where agency affiliation directly increases worker productivity on the job. Hence, while this alternative hypothesis is consistent with the first prediction, it is inconsistent with the second. By evaluating whether the predictions hold in the data, the analysis in the following sections distinguishes between the two possible agency-intermediation roles.

3 Hourly Wages

3.1 Agency affiliates receive an initial wage premium

Table 1 and Figure 3 (as an illustration for Web Programming) show that agency affiliates earn higher initial wages and that they differ from non-affiliates along other observable dimensions. This section applies the Oaxaca-Blinder method (Oaxaca, 1973; Blinder, 1973; Fortin et al., 2011) to decompose the log hourly wage on the first job into a component due to differences in observable characteristics and an "unexplained" component that is associated with agency affiliation. The wage of a non-affiliate worker i on his first job can be written as: $w_{i1} = X_i\beta_N + t + \varepsilon_i$, and the initial wage of an affiliate worker can be written as: $w_{i1} = X_i\beta_A + t + \varepsilon_i$, where the subscripts N and A indicate that the coefficients correspond to non-affiliates and affiliates, respectively. X_i are individual worker characteristics, including country and job category fixed effects, and t is a calendar time effect.[16]

[16] X_i also includes a constant term. Other characteristics included in X_i are: all measurable resume characteristics that can be easily quantified; the oDesk test scores that are observed in workers' profiles; and any work history from prior fixed-price jobs. Job category and worker country fixed effects are also included when the sample includes more than one group of each variable.

Estimates of the coefficients β_N and β_A are generated in separate regressions. The difference in the average initial wage earned by affiliates and non-affiliates that can be attributed to differences in observable characteristics is measured as $\left(\bar{X}_A - \bar{X}_N\right) \beta_N$, where $\bar{X}_A$ and $\bar{X}_N$ are the mean values of each column of X_i for affiliates and non-affiliates, respectively.[17] The remaining difference in initial wages, $(\beta_A - \beta_N) \bar{X}_A$, captures the fact that employers appear to value the same characteristics differently in affiliates and non-affiliates. This component can be attributed to agency affiliation or to other factors correlated with agency affiliation but excluded from X_i. The results from the wage decomposition are presented in Table 2, Panel A. Column 1 shows that the average initial log hourly wage for the 4179 affiliates in the sample is 1.913, compared to 1.611 for the 8614 non-affiliates in the sample. The agency premium, measured by $(\beta_A - \beta_N) \bar{X}_A$, is 47.7 percent of the 0.302 log wage difference.

The Oaxaca-Blinder decomposition depends on the choice of omitted category when multiple indicator variables, such as the worker country and job category fixed effects, are included among the observable characteristics (Fortin et al., 2011). The remaining columns of Table 2, Panel A restrict the sample to binary categories, alleviating concern over the excluded category.[18] These columns include new agency affiliates and non-affiliates from India and Russia, the two largest countries in the data, whose first jobs are in Data Entry, Web Design, and Web Programming. Column 2 shows that, for Data Entry, the log wage gap is 0.451, 85.6 percent of which can be attributed to agency affiliation. For Web Design, the log wage gap is 0.315, 68.5 percent of which can be attributed to agency affiliation. For Web Programming, differences in the observable characteristics, as valued at the rate implied by the wages of non-affiliates, suggest that agency affiliates would be paid a lower hourly initial wage if not for their affiliation. Because their wages exceed the wages of non-affiliates in India and Russia, agency affiliation is associated with more than 100 percent of the observed wage difference, at 121.5 percent.

This descriptive analysis demonstrates that employers are willing to pay higher initial wages to agency affiliates within narrowly-defined skill groups. This could be the result of agencies inter-

[17] This decomposition provides results relative to a baseline group. The most straightforward baseline for evaluating the impact of observable characteristics on affiliates' wages is to hold affiliates' characteristics constant, but to "weight" those characteristics as if they were evaluated for non-affiliates, by using the estimated coefficients β_N.

[18] For this reason, the observations in the job category-level analysis are restricted to workers in India and Russia only for all Oaxaca-Blinder decompositions throughout the paper. Elsewhere, the analysis includes workers from all countries in each specification and includes worker country fixed effects.

mediating in hiring, by providing information that affiliates are higher-quality, or intermediating on-the-job production, increasing worker productivity directly. Examining workers' first-job characteristics offers some insight to help distinguish between these roles. The data contain records indicating whether agency affiliates are hired by employers who simultaneously employ workers from the same agency or who have hired members of the same agency in the past. In both cases, a worker's agency affiliation may directly increase the value of a worker to a given employer, either because team coordination is easier within agency teams or because the agency has employer-specific knowledge that is useful on the job.

Approximately 43 percent of the sample of agency workers in these data are first hired by an employer in one of these categories. Table 2, Panel B reproduces the Oaxaca-Blinder wage decomposition shown in Panel A, restricting the sample to the 57 percent of affiliates who are not first hired by an employer with current or past experience with the same agency. There is a smaller wage gap between affiliates' and non-affiliates' wages in the restricted sample (0.153, compared to 0.302 in Panel A). Nonetheless, because these affiliates' other observable characteristics also differ from those of excluded affiliates, the percentage of the wage gap that is attributable to agency affiliation actually increases to 58.8 percent (compared to 47.7 percent in the panel above). This pattern is particularly pronounced in the Web Programming job category, where 180.3 percent of the observed wage difference can be attributed to agency affiliation rather than to differences in other observed characteristics.

Affiliates first hired for team-based projects and those hired by employers who have experience with the agency have higher wages than other affiliates. However, Table 3 shows that this is because workers from agencies with ongoing relationships with employers are, on average, highly paid relative to workers in other agencies. Within an agency, affiliates' first wages are unrelated to existing agency-employer relationships. Focusing only on affiliated workers, Panel A provides results from regressing the initial log wage on variables indicating whether the employer has current or past experience with the agency. The variable "teamwork" is constructed from hourly billing records and indicates that another agency member is billing time for the same employer on the same project within 30 days of the date of hire. The variable "number of prior agency hires" proxies for the amount of employer-specific information that an agency may have that is available to its affiliate workers. The estimated coefficients in Columns 1 and 2 reveal that teamwork is positively associated with initial affiliate wages.[19] In contrast, prior shared experience between the employer and agency does not appear to play any role in explaining higher initial affiliate wages.[20] Panel B, however, presents results that include agency fixed effects in the regression. The coefficient on teamwork is no longer significantly different from zero, suggesting that the premium associated with agency teamwork is due to variation in initial wages across agencies rather than to the fact that highly-paid affiliates are more likely to work in teams.

3.2 The agency premium declines as information is revealed

This section examines variation in the value of agency affiliation over the course of workers' careers to distinguish between agency intermediation roles. Under the hypothesis that public feedback substitutes for the information conveyed by agency affiliation, the wages of non-affiliates are predicted to increase more in response to good feedback. Hence, for workers that are revealed to be of similar quality by the end of the first job, as summarized in their feedback score, the premium an employer is willing to pay to hire an agency affiliate is predicted to decrease compared to the initial agency premium. In contrast, under the alterative hypothesis that affiliation increases on-the-job productivity, feedback is not differentially informative about worker quality. This hypothesis predicts a persistent agency premium and cannot explain why affiliates' wages might be less responsive to the feedback score received on the first job.

For all workers who were employed for at least two jobs, wage growth between the first and second job can be estimated as:

$$w_{i2} - w_{i1} = (F_{i1} + X_{i1} + E_i + \widetilde{Z}_{ij}) * (\delta + A_i\delta_A) + C_i + \widetilde{J}_{ij} + t_{i2} + \widetilde{\varepsilon}_i \qquad (1)$$

where w_{ij} indicates the log hourly wage worker i earned on job $j = 1, 2$. The term F_{i1} is the feedback score that worker i receives on the first job. X_{i1} includes the total hours worked on the first job;

[19] The estimated standard errors presented in Table 3 do not include an adjustment for any heteroskedasticity or clustering by affiliation status. Such an adjustment would likely increase the size of the standard errors, which means that the lack of a statistically significant association between initial wage and affiliation status is robust to this concern.

[20] These results suggest that agencies play a different role than that of the temporary staffing agencies studied in Bidwell and Fernandez-Mateo (2010), who find that the value of the employer-agency relationship increases over time, as the agency learns how to make higher-quality matches between employers and workers.

this attempts to account for learning—and productivity gains—on the job, which may be correlated with agency status. E_i measures the pre-oDesk experience of worker i, in terms of the number of years worked prior to joining the site. $\widetilde{Z}_{ij}$ contains information about job characteristics that may differ between jobs 1 and 2. Specifically, it includes a set of indicators that measure whether there is a change in team status or agency-team status (always zero for non-affiliates) between jobs. δ and δ_A are estimated coefficients, and A_i indicates whether worker i is agency-affiliated. Note that any time-invariant worker characteristic that is correlated with log wage levels is differenced out of the equation.[21]

Table 4 presents estimates of the predicted wage growth between jobs 1 and 2 for workers with different characteristics, based on the estimated coefficients from equation (1).[22] Panel A excludes $\widetilde{Z}_{ij}$ from the estimation. Column 1 shows the results for all surviving workers in all job categories.[23] For workers receiving a feedback score of 4.5 out of 5 on their first job, the predicted log wage change for affiliates is 0.142, compared to a change of 0.220 for non-affiliates. Overall, using the wage gap estimates from Table 2, good feedback on the first job closes 51 percent of the initial wage gap attributable to agency affiliation by the start of the second job.[24] For Web Programming (shown in Column 4), affiliates receiving a feedback score of 4.5 are predicted to receive an average increase in log hourly wages of 0.067. Non-affiliates receiving the same feedback score have a predicted average log wage increase that is almost three times as large, at 0.186.[25]

The estimated coefficients on other initial job characteristics (X_{i1}) suggest that hours spent on

[21] C_i includes worker-level indicator variables, consisting of a cohort fixed effect that controls for aggregate market conditions when workers find their first job, while capturing different transition rates to second jobs for more recently arriving cohorts, and country and job category fixed effects where appropriate. $\widetilde{J}_{ij}$ are further controls for the job characteristics of each job, the effects of which are not allowed to differ by agency status. t_{i2} are monthly dummies for the month the second job begins, to control for aggregate market conditions at the time of the second job. $\widetilde{\varepsilon}_i$ is a worker-level error term. The estimated equation also contains an indicator if the worker has not received feedback before the second job, interacted with agency affiliation, and an indicator if years of work experience are missing, interacted with agency affiliation.

[22] The estimated coefficients, δ and δ_A, are presented in Appendix Table 2. Standard errors in Table 4 and Appendix Table 2 are clustered by agency-affiliation status because the variance of the initial log wage and the variance of the change in log wage are smaller for agency affiliates. To correct the resulting small number of clusters problem, p-values are computed using a t-distribution with a degrees-of-freedom correction (Donald and Lang, 2007).

[23] 67 observations were excluded because of large wage decreases between jobs; oDesk's management suspects that these indicate that a share of the wages earned were paid offline to avoid payment of the oDesk commission.

[24] This is calculated as $\frac{-0.073}{0.302 \times 0.477}$, where 0.073 is the difference between non-affiliates' and affiliates' wage growth, 0.302 is the initial wage gap between affiliates and non-affiliates, and 0.477 is the percentage of the wage gap that is not explained by differences in characteristics.

[25] While the estimated coefficient on the interaction of affiliation and feedback is not significant (see Columns 7 and 8 in Appendix Table 2), the difference in log wage growth for affiliates and non-affiliates at a feedback score of 4.5 is negative and significant, as shown in Table 4, Column 4.

the first job are not related to wage growth, either on average or differently for affiliates and non-affiliates (as shown in Appendix Table 2). While years of prior experience off the site are negatively correlated with wage growth (as we would expect, given that wage growth for all workers may also reflect productivity growth, which is likely to be concave in the experience level), this estimated effect is weaker for affiliates. Hence, these effects cannot explain why non-affiliates' wages grow more after the first job.

Table 4, Panel B presents the results of the estimation, including the variables related to changing job characteristics between jobs 1 and 2: the $\widetilde{Z}_{ij}$ in equation (1). Including the change between team-based jobs, the change in agency team-based jobs, and agency affiliation interacted with the change in team-based jobs illustrates whether differential wage growth is, for example, due to the fact that agency affiliates on their first job are likely to work in teams and then do not receive the wage premium associated with this teamwork on the second job. Panel B shows that team changes have very little effect on wage changes for agency-affiliated workers. Specifically, the difference in wage growth for affiliates and non-affiliates receiving a good feedback score is -0.119 in Panel A and -0.120 in Panel B, where Panel B also controls for differences in propensities to work on teams. The impact of team-based work is not statistically different from zero for agency workers in any of the columns.

Nonetheless, this panel does reveal some evidence of differences in the wages associated with teamwork for affiliates and non-affiliates. Under the assumption that workers' pay is proportional to their marginal product of output, non-affiliates' wages are negatively related to teamwork (as shown by the negative coefficient on changes in teamwork of -0.068 in Column 1 and -0.044 in Column 4). The analogous coefficient for affiliates is the sum of the three estimates related to changes in agency teamwork, teamwork, and affiliate work on non-agency teams, which is insignificantly different from zero. This suggests that shared agency affiliation may enable more productive teamwork among workers, compared to teamwork among groups of other workers that are hired by the same employer. Overall, however, accounting for differences in the propensity to work in teams does not affect the differential relationship between feedback and wage growth for affiliates and non-affiliates.[26]

[26] The agency team premium is interpreted as the difference in within-agency team-based work compared to other team-based work. This is the right comparison because team-based projects likely differ systematically from individual projects. If instead the agency premium is interpreted simply as an indicator for within-agency team-based work, the coefficient in the wage change regression for all job categories on within-agency team-based jobs is 0.043

Figure 4 investigates the robustness of this result by presenting non-parametric evidence that non-affiliates' wages increase more than affiliates' wages after good feedback. The top panel shows the results of using a local polynomial estimator to separately regress wage changes for Web Programming workers on feedback for affiliates' and non-affiliates' first jobs. The bottom panel of Figure 4 shows that feedback is highly skewed, and the modal feedback score is 5 out of 5. The top panel shows that having received a feedback score of at least 2.25, non-affiliates' wages increase by more than affiliates' wages on the second job. For workers who received a feedback score of 5 out of 5 in Web Programming, the average log wage increase for non-affiliates is 0.16, compared to 0.10 for affiliates.

The result of this differential wage growth can be seen in wage levels for experienced workers. Table 5, Panel A presents summary statistics about worker characteristics for the group of workers with more than three prior oDesk jobs who were hired for at least one additional job by December 28, 2009.[27] The data in the first two columns show that, overall, affiliates continue to earn a significantly higher hourly wage than non-affiliates. However, looking within job categories, in Data Entry and Web Programming, experienced non-affiliates receive slightly higher hourly wages than experienced affiliates.[28]

Table 5, Panel B presents the Oaxaca-Blinder wage decomposition for all experienced workers, and then for experienced workers in the three most popular job categories for workers in India and Russia. These results are comparable to the same specifications for initial hourly wages shown in Table 2, Panel A. The first column indicates that the difference in the log hourly wage between the 2446 experienced affiliates and the 5046 experienced non-affiliates in the sample can be attributed mainly to differences in observable characteristics other than agency affiliation. Only 17 percent of the wage difference is unexplained by other observable characteristics, compared to 48 percent of

(Appendix Table 2, Column 2). It is significant at the 10% level. For Web Programming, the coefficient is 0.035; it is not statistically different from zero. Appendix Table 3 provides a more detailed analysis of the effect of team work on wage growth, allowing the effect of starting on a team and moving to independent work to differ from the effect of starting independently and moving to a team. These specifications indicate that the relationship between agency status and the responsiveness of wages to feedback is unaffected by transitions to and from teamwork.

[27] Because the data contain the oDesk careers of individual workers, this sample includes some experienced workers who received their first job prior to the beginning of the sample on August 1, 2008. This date was the first date included in the sample of initial wages studied in the previous subsection because the database began to record agency affiliation at this time.

[28] One further notable fact is that the feedback score for experienced non-affiliates tends to be slightly higher than the feedback score for experienced affiliates.

the initial wage difference.

In the job-category-level analysis, now restricted to workers in India and Russia (whereas Panel A includes workers from all countries), affiliates in Data Entry and Web Design have an even larger wage premium than for inexperienced affiliates (Table 2, Panel A), and the proportion of the premium attributable to agency affiliation is even larger in Web Design for experienced workers than for inexperienced workers. However, for workers in Web Programming, the average wage difference between experienced affiliates and non-affiliates in India and Russia is around one third as large as the difference in initial wages, at 0.056 compared to 0.147 in Table 2, Panel A. Moreover, the share of this difference attributable to agency affiliation is less than half as large for experienced workers, at 50 percent, compared to 122 percent for inexperienced workers.

4 First Job Outcomes and Survival Probabilities

4.1 The initial agency wage premium reflects differences in realized job outcomes

oDesk collects detailed internal survey data from employers about job outcomes. These data allow a direct test of whether the affiliate wage premium reflects actual productivity differences. Table 6, Panel A presents the results of a Oaxaca-Blinder decomposition in which the dependent variable is a binary measure indicating whether the employer reported that the first job was a success.[29] Agency affiliates' first projects are, on average, more successful than non-affiliates' projects. Column 1 shows that the mean difference in reported success across all job categories is 0.03 (=0.61 - 0.58), 97.5 percent of which is attributable to agency affiliation. For Web Programming workers in India and Russia, 64.2 percent of agency affiliates' first jobs, versus 56.9 percent of non-affiliates' first jobs, are successful. 62.5 percent of this difference is attributable to agency affiliation.

The dependent variable in Panel B is the log of the number of hours worked on the first hourly job. An employer has the option to end an assignment at any time after hiring a worker. The

[29] The decomposition procedure here is modified slightly from Section 3.1 to account for differences in expected first-job difficulty that may be correlated with agency status. Additional attributes of each job opening are included in the controls. These controls are the expected project duration (dummy variables for all combinations from the set {number of weeks, part-time or full-time}) and the level of detail in the job-opening announcement (the number of alpha-numeric characters in the job description).

expected project duration is included as a control variable in the decomposition, so variation in the length of time worked is likely to reflect employer satisfaction with the work performed up to the end of the employment period.[30] The data in Table 6, Panel B reveal that agency affiliates have much longer first jobs. The overall difference in log hours worked, shown in Column 1, is 0.684 (=3.658 - 2.973), of which 53.2 percent cannot be explained by observable job or worker differences. Columns 2 to 4 of Table 6, Panel B show that this difference is present within the three main job categories, and that affiliation explains the largest share of the difference in project duration in Web Programming jobs (at 100.2 percent).

Table 7 shows that agency teamwork or prior agency-wide interaction for affiliated workers cannot explain affiliates' more successful outcomes on the first job. Panel A demonstrates that agency affiliates working in teams on their first jobs are more likely to be successful, particularly in Web Programming in India and Russia. However, as in the first hourly wage analysis in Table 3, including agency fixed effects reveals that the higher success rate associated with agency teamwork occurs because members of more-successful agencies tend to work in teams. As in the hourly-wage analysis, prior agency-employer interaction is not related to the success rate, either across or within agencies.[31]

4.2 The lowest-quality non-affiliates are less likely to find a second job

There are two possible selection-based explanations that may contribute to wage convergence: The lowest-quality non-affiliates or the highest-quality affiliates are being selected out of the market after being first hired. To analyze which of these effects is present in the data, the probability that worker i is employed for a second job is written:

$$1_i(\text{2 or more jobs}) = (X_{i1} + F_{i1}) * (\phi + A_i \phi_A) + JC_{i1} + C_i + \varepsilon_i \tag{2}$$

[30] One alternative reason for variation in project length after controlling for expected duration is that workers complete the project faster or slower than anticipated. Under this explanation, duration is likely to be negatively correlated with worker quality. However, the project-length variable is positively correlated with employer-reported project success, suggesting that this variable is also positively correlated with worker quality.

[31] Overall, teamwork is associated with an increased probability of success of six percent (seven percent for Web Programming in India and Russia). For Data Entry, affiliates working in teams are actually less likely to be successful than affiliates from the same agency working alone.

where the dependent variable is equal to 1 if worker i was employed for a total of two or more jobs in the data. X_{i1} is a vector of worker and first-job characteristics including a constant term. F_{i1} is the feedback received by worker i on the first job. ϕ and ϕ_A are estimated coefficients, and A_i indicates whether worker i is agency-affiliated.[32]

Table 8 presents a subset of the estimated coefficients from linear probability estimates of equation (2). Panel A excludes the variable F_{i1} from the empirical specification. As predicted, given the fact that affiliates' first jobs are more successful, affiliates are significantly more likely to be employed for a second job. Columns 2 to 4 show that the effect is particularly strong for the Data Entry and Web Programming job categories.

To assess whether the probability of finding a second job is related to information revelation on the first job, Panel B includes feedback on the first job, F_{i1}, in equation (2). Including the interaction of the feedback score on the first job and an agency affiliation indicator permits flexible estimation of whether the information revealed from prior jobs has a smaller effect on the probability that an affiliate finds a second job compared to the same probability for non-affiliates.

The coefficient on agency affiliation indicates that the baseline propensity to be re-employed is much higher for agency affiliates. This coefficient from the linear probability model is 0.20 for all job categories and 0.25 for Web Programming. Including feedback, however, dramatically increases the probability that workers with good feedback are re-employed—and especially for non-affiliates. While good feedback is valuable for all workers, the negative and significant coefficient on the interaction of affiliation and feedback in Web Programming (Column 4) suggests that the new information contained in the feedback score is larger for non-affiliates in this job category. The last row of Panel B evaluates differences in re-employment probability at a feedback score of 4.5 for affiliates and non-affiliates. For workers who received a feedback score of 4.5, the overall difference in re-employment probabilities between agency affiliates and non-affiliates falls by 40 percent, from 0.20 to 0.12. In Web Programming, the difference in re-employment probabilities falls by 68 percent.[33] Low-quality non-affiliates, whose quality has been revealed in their feedback scores,

[32] As in equation (1), C_i are monthly cohort fixed effects and JC_{i1} are controls for first job characteristics, where the effects on the probability of being rehired do not vary with agency status, and ε_i is a worker-level error term.

[33] As a robustness check, equation (2) was re-estimated including the wage received on the first job. The estimated specification is: $1_i(2ormorejobs) = (X_{i1} + F_{i1} + w_{i1}) * (\phi + A_i\phi_A) + JC_{i1} + C_i + \varepsilon_i$.Other worker-level attributes observable at the time of first hire were also included in X_{i1}. The results, shown in Appendix Table 4, reveal statistically differential re-employment rates based on initial wages in the "all job categories" columns, but the

are selected out of the market.

Similar to the inferences drawn from Tables 3 and 7, Table 9 shows that variation in the probability of affiliated workers finding a second job is associated with having worked in an agency team on the first job, but that this is an across-agency finding. Affiliates of agencies where workers tend to be employed in teams are more likely to be rehired, whether or not an affiliate works on a team in his first job.

5 Evidence from Firms' Hiring Choices

The worker-level findings in the previous two sections reveal that affiliation is valuable to a worker only prior to quality-revelation on the job. Implicit in this analysis is the fact that the wage earned is positively correlated with a worker's expected marginal product. The detailed nature of the oDesk data enables a direct test of whether agency affiliation is associated with the likelihood that a given worker is hired and, by implication, with the value an employer expects to gain from hiring a worker in this market. The relationship between the probability that an applicant is hired and the applicant's characteristics, including agency affiliation, can be estimated using a conditional logit model. Indexing job openings by j, the firm that posts job opening j chooses one applicant i from the choice set I_j, where the size of the choice set varies across openings.[34] Alternative $i = 0$ allows the firm to leave the market without hiring. The employer's payoff from choosing a given applicant is: $U_{ji} = \alpha + z_i\beta + \varepsilon_{ji}$ for $i > 0$, where z_i are variables related to the employer's information about worker quality (at the time the job is posted), including the wage-rate bid. The error term ε_{ji} is

magnitude is economically small. A one standard deviation increase in initial log wages for agency-affiliated workers reduces the probability of re-employment by about .03. This is only 4% of the agency affiliate's baseline probability of surviving onto a second job. There is no statistically significant difference in the probability of finding a second job as a function of initial wages in any individual job category, including Web Programming.

Appendix Figure 1 illustrates the estimated probability that affiliates and non-affiliates find a second job as a function of the wage on the first job for workers in Web Programming. The estimates are constructed using a kernel-weighted local polynomial regression where the dependent variable is an indicator that the worker finds a second job. This dependent variable is regressed on the log hourly wage on the first job. Because the estimation procedure requires many observations in a neighborhood around each log wage value, countries are pooled together, and the log hourly wage on the first job is net of the country-specific mean Web Programming wage. The difference in the probability that affiliates and non-affiliates find a second job does not appear to systematically differ as a function of the wages received on the first job for either affiliates or non-affiliates in areas of the wage distribution with many data points.

[34] Openings where employers initiate some candidacies are excluded to maintain the comparability of the information the employer has about each applicant in the choice set. This exclusion also makes it less likely that employers know workers offline or from prior assignments.

assumed to follow a type I extreme value distribution.

The worker characteristics included in z_i are: an agency-affiliation dummy; an indicator if the worker has been hired for exactly one prior job; an indicator if the worker has been hired for at least two prior jobs; and interaction terms for each of these indicator variables with agency affiliation. The model is estimated using two different definitions of agency affiliation. A worker's outsourcing agency is defined as "established" if agency workers have been employed, in total, for four or more jobs. A worker is affiliated with a "well-established agency" if members of the agency have collectively worked on at least 34 jobs.[35] The variable indicating that the worker has been hired once captures the fact that he has likely received a feedback score, so his quality has been revealed. The variable indicating that the worker has been hired at least twice captures the fact that the worker is likely to have received good feedback scores because he has been re-hired at least once after the first job.

Under the hypothesis that agency affiliation signals that a worker is high-quality and that feedback received on the job substitutes for this information, employers attribute value to agency affiliation only for inexperienced workers. Thus, the estimated coefficient on agency affiliation is predicted to be positive, and the estimated coefficients on the interaction terms with experience are predicted to be negative. For experienced workers with two or more prior jobs, the sum of the estimated coefficients on the agency-indicator variable and the interaction of the agency-indicator variable with the variable indicating public knowledge that a worker is high-quality is predicted to be insignificantly different from zero.

Table 10 presents the conditional logit results for employers posting job openings in Web Programming.[36] There is a positive and significant coefficient on the variable indicating that a worker has been employed for at least two prior jobs (the Revealed High-Quality variable) in each specification. This suggests that employers value workers with at least two prior jobs more highly, consistent

[35] These cutoffs correspond to the median and 90th percentile of the jobs-per-agency distribution. This agency categorization ensures that an agency-level feedback score is observable by employers.

[36] The likelihood function is given by $L = \prod_j P_0^{y_{j0}} P_1^{y_{j1}} P_2^{y_{j2}} ... P_{I_j}^{y_{jI_j}}$. The y_{ji} is a $((I_j + 1) \times 1)$ vector indicating the alternative chosen in opening j. The probability that each alternative i is chosen is given by $P_i = \frac{1}{\sum_{k \in I_j} e^{z_{jk}\beta - z_{ji}\beta}}$. The log likelihood is then $\ln L = \sum_j \sum_{i \in I_j} y_{ji} \ln P_i$. The probability that alternative i is chosen is generated by pairwise comparisons between the alternative i and alternatives $-i$. The constant α is identified from likelihood components involving $e^{z_{j0}\beta - z_{ji}\beta}$ or $e^{z_{ji}\beta - z_{j0}\beta}$. The estimated parameter value α can be interpreted as the average relative value of choosing a worker on oDesk who has no observable characteristics versus the outside option.

with the market selecting to rehire only high-quality workers for a second job. The estimated coefficients on the wage rate bid are negative and significant, revealing that—as expected—firms prefer to pay lower wages.

The results in Columns 1 and 2 are consistent with the predictions of the information-provision agency role. Employers positively value affiliation with an agency, particularly a well-established agency. Also as predicted, the estimated coefficients on the interaction of the indicators of agency affiliation and prior experience are negative and significant. In each case, the sum of the estimated interaction coefficient and the estimated coefficient on agency affiliation is insignificantly different from zero. For affiliates with at least two prior jobs, affiliation ceases to be valuable.[37]

Columns 3 and 4 of Table 10 split the sample by whether the employer posts multiple job openings around the same time as the job opening in question. This allows an examination of whether agency affiliation is valuable to employers because agencies coordinate staffing on teams or because agencies provide information. The potential for complementarities arising from teamwork facilitated by agency affiliation is likely to be greater if the employer is searching for multiple workers. While the agency premium is greater for inexperienced affiliated workers hired by an employer who is hiring other workers from the same agency, the negative interaction between revealed quality and affiliation is also larger in magnitude for hires made by this group of employers (-1.284 in Column 3, compared to 0.971 in Column 4). These findings are consistent with the hypothesis that, while affiliates from agencies that engage in teamwork are higher quality than affiliates from other agencies (as shown in the across-agency analysis in Tables 3, 7 and 9), the additional information that agency affiliation provides about worker quality for the subset of workers joining teams is less useful once affiliates' quality is revealed on the job.

[37] The association between agency affiliation and the likelihood that an employer makes a hire could result from the fact that agency affiliates are better able to distinguish and, hence, apply to jobs where a hire is more likely to be made. For this explanation to also explain the interaction results, it would have to be that only inexperienced affiliates were able to do this. Nonetheless, to investigate this possibility, Appendix 3 presents an analysis of whether applicants tailor their application behavior to employer characteristics, including whether a hire is made. There is no evidence of this in the data. Affiliates and non-affiliates neither bid lower wages nor bid more quickly for openings where the employer subsequently makes a hire. In fact, employers are less likely to make a hire when receiving a large number of applications (from affiliates and non-affiliates) in the few hours after posting the job. These results are shown in Appendix Tables 5 and 6.

6 Conclusion

This paper presents evidence that organizations have sprung up to intermediate between employers and workers in online labor markets by providing information about worker quality. Affiliation with one of the many small independent outsourcing agencies on oDesk.com is valuable at the start of a worker's career: Inexperienced affiliates earn higher initial wages and are more likely to be hired than similar non-affiliates. However—and particularly for workers in the highly-skilled Web Programming job category—agency affiliation is much less valuable for workers with experience. The analysis also shows that non-affiliates' wages in Web Programming are more responsive than affiliates' wages to the feedback scores received on the job, implying that more information is contained in these scores for non-affiliated workers. This is supported by evidence from firms' hiring choices, revealing that affiliation is valuable to employers only before worker quality has been revealed on the job. Thus, affiliation credibly signals that inexperienced workers are high-quality, preempting on-the-job quality discovery.[38] One important implication of the findings shown here is that agencies have a large positive impact on both transactions' volume and value by increasing the number of known high-quality workers in the market.[39]

By demonstrating how intermediaries have arisen to perform this role, the findings suggest that incomplete information hampers trade in labor-offshoring markets. Therefore, this study complements the empirical literature on incomplete information in online consumer-product markets, in which the product being sold is analogous to the labor services provided by an oDesk worker.[40] Several other recent related papers study the role of social networks in providing information about online investment quality. Agrawal et al. (2011) suggest that investors sharing personal connections to unsigned music artists are less responsive to others' investment decisions because they have

[38] According to oDesk.com's senior management, the infrastructure built to accommodate agencies within the oDesk market was not designed for this purpose. Rather, the aim was to increase the number of workers on the site by creating incentives for existing workers to encourage new workers to sign up.

[39] Agencies increase output in two related ways: They increase the expected quality of workers hired on the first job (on the intensive margin). They also increase the number of known high-quality workers, who are more likely to be re-hired for subsequent jobs (on the extensive margin).

[40] Lewis (2011) examines the role of voluntary information disclosure in defining explicit contracts between buyers and sellers regarding the quality of used cars sold on eBay Motors. Luca (2010) shows that restaurant revenues respond more strongly to online restaurant reviews that are more informative. Resnick and Zeckhauser (2002) and Bajari and Hortacsu (2004) discuss the economics of internet auctions and summarize the empirical evidence on the relationship between the information contained in seller feedback and price. Other studies of online labor markets discuss different methods by which information is credibly shared; see Horton (2010) for a discussion of the features of online labor markets. Bagues and Labini (2009) show how mandatory disclosure of quality-relevant worker information affects worker outcomes such as unemployment duration, wages, and job satisfaction.

informational advantages about the artist's quality. In their study of the loan market Prosper.com, Freedman and Jin (2010) find that borrower affiliation with a social network is not associated with borrower quality. They propose that this is due to characteristics of the market design, which limit incentives for group founders to grant membership only to good-quality borrowers.[41]

The findings also indicate that for the tasks posted on the site, disintermediation of traditional firm-like organizations is entirely feasible. Once the employer hires a high-quality worker, tasks can be completed successfully without requiring additional intermediation to increase worker productivity. That is, the employer and worker do not appear to need any additional inputs from a third-party organization to either coordinate tasks across workers or to increase worker output directly.[42] Even in tasks that are likely to require coordination, such as those tasks performed by teams of Web Programmers, the oDesk marketplace appears to successfully disintermediate managers.

Two factors constrain agencies' growth and, in doing so, agencies' ability to fully resolve trade frictions arising from incomplete information. Members of the same agency tend to share many observable characteristics and appear to know each other offline. This suggests that offline social ties among groups of remote workers enable quality screening.[43] The size of any one agency is thereby restricted by the size of each agency head's personal offline network. The mechanisms outlined in the paper also indicate that there are limits to the number of potential new agencies. Since affiliation is fixed throughout a worker's career, new agencies can be formed only by the relatively small number of good-quality non-affiliates who are fortunate enough to be hired and, as a result, have their quality revealed.[44] Therefore, outsourcing agencies' growth may be outpaced by both the growing demand for offshore services and the corresponding demand for information about service providers' quality.

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[41] In the oDesk setting, an agency head has a strong incentive to maintain the average feedback score (and, because of this, affiliate quality) within the agency since he collects a fraction of the revenues earned by all other agency affiliates over their entire oDesk careers.

[42] While recent work has established that local services that are complementary to internet use and labor skills increase the wage gains from internet adoption across the U.S. (Forman et al., 2011), providing complementary services that increase on-the-job productivity is not the primary role of the intermediaries studied here.

[43] Montgomery (1991) describes how referrals from current employees connected to a social network lead to subsequent hiring from the same network. Casella and Hanaki (2006, 2008) show how costly signaling of worker quality can substitute for finding employment through a personal connection. Our data mirror the assumption made in Saloner (1985) that "Old Boy Networks" have pre-existing information about worker quality. These social ties enable quality signaling.

[44] Over the time period studied, the number of hires made on oDesk grew at an average of 10 percent per month. However, the share of jobs for which inexperienced workers were hired fell by an average of 0.2 percent per month.

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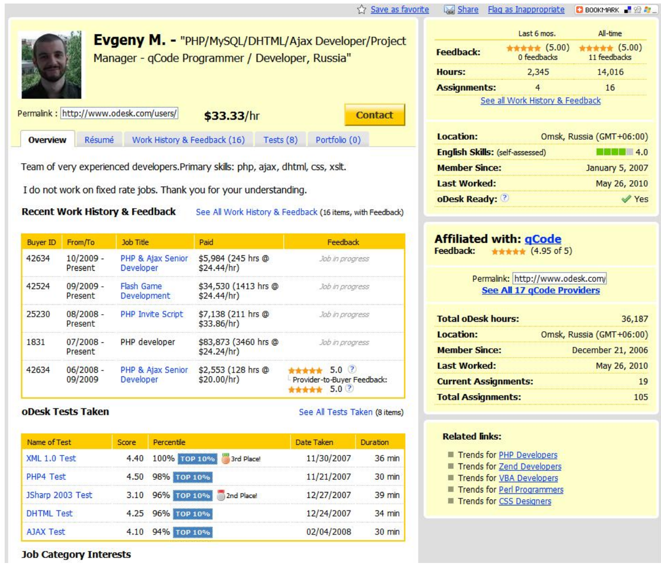

Figure 1: A sample worker profile. The feedback score is in the top right corner, and the agency brand appears as "qcode." The work history on recent jobs is visible in the middle of the screen.

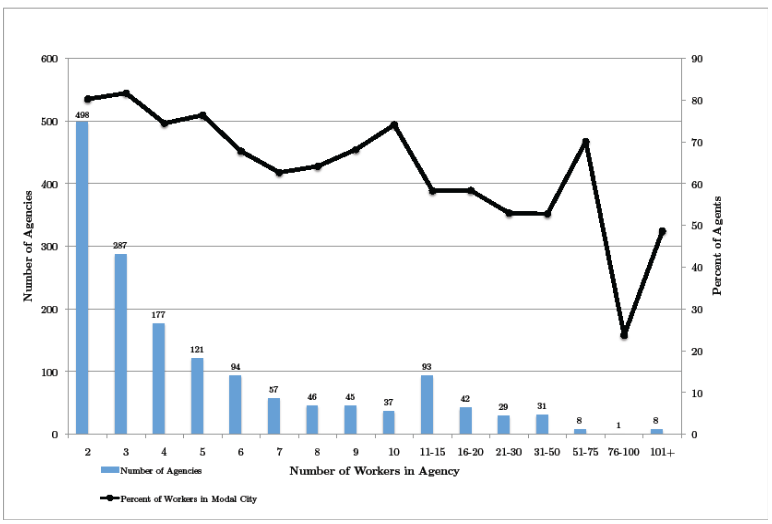

Figure 2: The number of agencies (by size) and the concentration of workers in the agency's modal city. The modal-city measure underestimates geographic concentration because workers may enter different spellings of the same city or may be located in suburbs and nearby towns.

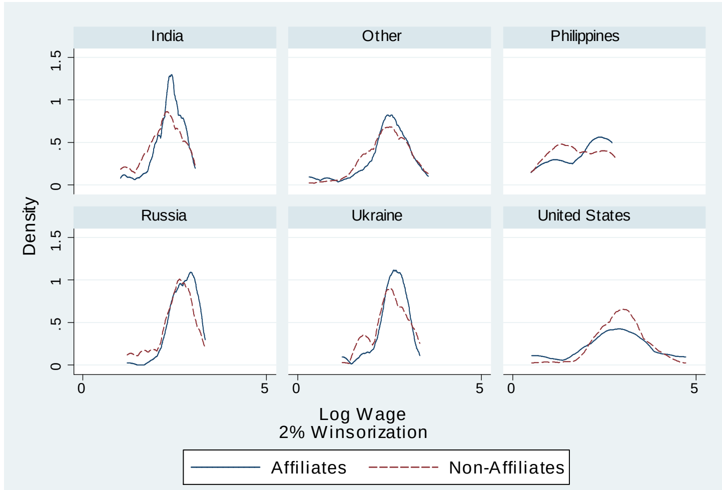

Figure 3: Density of log wages on the first hourly job in Web Programming by country. Wages are winsorized at the 2 % level by country.

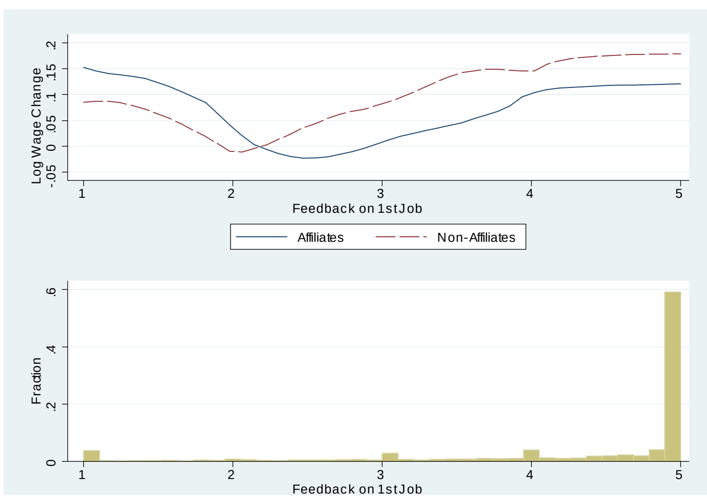

Figure 4: The top panel provides the relationship between log wage changes and feedback on the first job. Workers without feedback on the first job are excluded. The figures are constructed from Kernel-weighted local polynomial smoothed estimates. The bottom panel is a histogram of feedback scores on the first job.

Table 1: Summary Statistics for Workers Hired on oDesk

	Non-affiliates	Affiliates	Non-affiliates	Affiliates	Non-affiliates	Affiliates	Non-affiliates	Affiliates
Panel A. By Job Category:	All Job Categories		Data Entry		Web Design		Web Programming	
Number of Workers Hired (for at least one job)	8614	4179	952	298	413	479	982	1223
Percentage of Total Bidders Hired	8	35	4	26	5	25	14	45
Good English Skills Indicator	0.87	0.82**	0.87	0.89	0.86	0.82	0.79	0.79
BA Degree or Higher	0.40	0.35**	0.41	0.39	0.37	0.32	0.36	0.32**
Taken One or More Tests Indicator	0.78	0.59**	0.82	0.66**	0.77	0.60**	0.70	0.55**
Log Hourly Wage on First Job	1.61	1.91**	0.29	0.31	2.09	2.23**	2.42	2.41
Standard Deviation of Initial Log Wage	(1.13)	(1.00)**	(0.96)	(0.79)	(0.82)	(0.54)**	(0.70)	(0.62)**
Panel B. By Country:	India		Russia		Philippines		US	
Number of Workers Hired (for at least one job)	1188	1850	186	204	2376	590	2418	255
Percentage of Total Bidders Hired	8	36	17	58	9	51	6	17
Good English Skills Indicator	0.83	0.83	0.64	0.63	0.93	0.91	0.87	0.91
BA Degree or Higher	0.40	0.33**	0.23	0.21	0.49	0.47	0.35	0.33
Taken One or More Tests Indicator	0.66	0.51**	0.70	0.60**	0.89	0.81**	0.77	0.68**
Log Hourly Wage on First Job	1.62	2.03**	2.53	2.72**	0.71	0.90**	2.19	2.34**
Standard Deviation of Initial Log Wage	(0.98)	(0.82)**	(0.51)	(0.36)**	(0.82)	(0.77)**	(1.01)	(1.19)**

Notes: The sample is workers on their first hourly hire, broken down by job categories (top panel) and countries (bottom panel), for workers whose first job applications occurred between 8/1/2008 and 12/28/2009. Asterisks ** indicate that t-tests reject equality of the means for the non-affiliates' and affiliates' values at the 5% level. For the standard deviation of log wage, asterisks ** indicate that F-tests of differences in variance reject equality of variances at the 5% level.

Table 2: Oaxaca-Blinder Decompositions of Mean Differences in Log Initial Wages

	All Job Categories All Countries (1)	Data Entry India and Russia (2)	Web Design India and Russia (3)	Web Programming India and Russia (4)
Panel A. First Hourly Hire (all inexperienced workers)				
Data:				
Number of Affiliates	4179	94	299	738
Number of Non-Affiliates	8614	84	114	330
Mean Log Hourly Wage: Affiliates	1.913	0.396	2.255	2.401
Mean Log Hourly Wage: Non-Afiliates	1.611	-0.055	1.940	2.253
Mean Difference in Log Hourly Wage between Affiliates and Non-affiliates	0.302	0.451	0.315	0.147
Decomposition Results:				
% Due to Agency Affiliation, Unexplained by Characteristics	47.7	85.6	68.5	121.5
Panel B. First Hourly Hire (excluding affiliates hired by employers with current or past same-agency experience)				
Data:				
Number of Affiliates	2393	53	161	371
Number of Non-Affiliates	8614	84	114	330
Mean Log Hourly Wage: Affiliates	1.764	0.412	2.191	2.327
Mean Log Hourly Wage: Non-Afiliates	1.611	-0.055	1.940	2.253
Mean Difference in Log Hourly Wage between Affiliates and Non-affiliates	0.153	0.467	0.251	0.074
Change from Panel A from Excluding Teams and Coordination	-0.149	0.016	-0.064	-0.073
Decomposition Results:				
% Due to Agency Affiliation, Unexplained by Characteristics	58.8	72.7	63.3	180.3

Notes: An observation is a unique worker on his first hourly-paying job. The sample includes all workers whose first job application occurs between 8/1/2008 and 12/28/2009. The difference in log wages due to agency affiliation is given by the difference in coefficients evaluated at the mean of the affiliate characteristics. The Oaxaca-Blinder decompositions are computed using the non-affiliate "coefficients" as the base case. All columns contain a variety of controls. Continuous variables included as controls are: the number of prior fixed price hires; revenue and feedback on prior fixed-price jobs; years of pre-oDesk experience; and test scores in a variety of categories. Month dummies are included to capture differences in the market over time.
Dummies are included for: reporting good English skills, reporting a BA or higher degree, reporting programming experience, missing test scores in each category, and missing experience. Column 1 contains dummy variables for each country and job category. Columns 2 through 4 restrict the sample by job category and only include workers in India and Russia (hence, the number of workers in each category differs from Table 1). A dummy variable for India is included in these specifications. The second panel includes the subset of all affiliates who are employed by an employer with no current or past experience hiring another affiliate from the same agency.

Table 3: Log Initial Wage Regressions for Agency-Affiliated Workers, Across and Within Agencies

	All Jobs All Countries		Data Entry India and Russia		Web Design India and Russia		Web Programming India and Russia	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. OLS Regressions Across Agencies								
Teamwork	0.10***	0.10***	0.03	0.05	0.08	0.06	0.06	0.09**
	(0.02)	(0.02)	(0.10)	(0.11)	(0.06)	(0.08)	(0.04)	(0.04)
Number of Prior Hires for Agency-Employer Pair		0.00		0.00		-0.04		0.00
		(0.00)		(0.00)		(0.03)		(0.00)
Interaction of Teamwork and Prior Agency-Employer Hires		-0.00		-0.01		0.02		-0.01*
		(0.00)		(0.01)		(0.03)		(0.01)
Number of Workers	4179	4179	298	298	479	479	1223	1223
R-squared	0.62	0.62	0.47	0.47	0.29	0.30	0.26	0.27
Panel B. Regressions with Agency Fixed Effects								
Teamwork	0.03	0.03	0.15	0.15	-0.06	-0.07	-0.05	-0.03
	(0.02)	(0.02)	(0.12)	(0.12)	(0.08)	(0.10)	(0.03)	(0.03)
Number of Prior Hires for Agency-Employer Pair		-0.00		0.02		-0.01		-0.00
		(0.00)		(0.02)		(0.03)		(0.10)
Interaction of Teamwork and Prior Agency-Employer Hires		-0.00		-0.02		0.01		0.00
		(0.00)		(0.03)		(0.03)		(0.01)
Number of Workers	4179	4179	298	298	479	479	1223	1223
R-squared	0.91	0.91	0.94	0.94	0.87	0.87	0.89	0.89

Notes: Standard errors in parentheses, and *** p<0.01, ** p<0.05, * p<0.1. An observation is a unique worker on his first hourly-paying job. The sample includes all outsourcing agency affiliated workers whose first job application occurs between 8/1/2008 and 12/28/2009. The dependent variable is the log hourly wage. In Panel A, regressions are across agency. Teamwork is an indicator that the worker was matched to a project with another agency worker simultaneously matched with the employer. Number of Prior Hires for Agency-Employer Pair counts the prior pairs of workers for the agency-employer pair. In Panel B, fixed effects for each agency are included. All columns contain the same controls as the wage decomposition shown in Table 2.

Table 4: Change in Hourly Wage between First and Second Jobs, Linear Combinations of Estimated Coefficients

	All Job Categories (1)	Data Entry (2)	Web Design (3)	Web Programming (4)
Panel A. Log Wage Change between First and Second Job				
Agency Affiliate Wage Change at 4.5 Feedback	0.142**	0.945***	-0.014	0.067
	(0.004)	(0.003)	(0.064)	(0.017)
Non-Affiliate Wage Change at 4.5 Feedback	0.220**	0.822**	0.128	0.186**
	(0.006)	(0.029)	(0.112)	(0.013)
Difference between Affiliates and Non-Affiliates at 4.5 Feedback	-0.073**	0.122	-0.14	-0.119**
R-squared	0.050	0.127	0.123	0.076
Panel B. Log Wage Change, Including Team Controls				
Difference between Affiliates and Non-Affiliates at 4.5 Feedback	-0.073**	0.122	-0.139	-0.120**
Agency Team Work Change (Dummy)	0.043*	0.0102	0.050	0.035
	(0.007)	(0.017)	(0.024)	(0.011)
Team Work Change (Dummy)	-0.068**	-0.137**	0.001	-0.044**
	(0.001)	(0.007)	(0.007)	(0.003)
Agency Affiliated Worker x Team Work Change	0.030***	-0.118***	-0.067	0.126
	(0.001)	(-0.001)	(0.017)	(0.008)
Agency Affiliates' wage change due to change in Team Work	0.003	-0.153**	-0.015	0.004
	(0.007)	(0.011)	(0.013)	(0.006)
R-Squared	0.053	0.138	0.126	0.079
Observations	8227	870	615	1463
Number of Affiliates	3086	265	341	887
Mean Wage Change for Affiliates	0.110	0.317	0.044	0.08
Mean Wage Change for Non-Affiliates	0.148	0.341	0.089	0.100

Notes: Because the variance in log wage growth is smaller for affiliates, robust standard errors (in parentheses) are clustered by agency status, and *** p<0.01, ** p<0.05, * p<0.1. The p-values are computed using a t-distribution with a degrees of freedom correction because of the small number of clusters, a solution suggested by Donald and Lang (2007). An observation is a unique worker who has two or more hourly jobs and whose first job application occurs between 8/1/2008 and 12/28/2009. 67 observations where wages declined by more than 70% were excluded because these workers are likely paid off the platform (disintermediation).
The dependent variable is the change in log wages between jobs. All specifications contain feedback on the first job, 1(Agency Member)*feedback, 1(Feedback not received by second job), 1(Agency Member)*1(Feedback not received by second job), hours worked between jobs, agency membership interacted with hours worked, pre-oDesk years of experience, agency membership interacted with prior experience, and first job characteristics. Job opening controls include the number of alpha-numeric characters in the vacancy announcement and a full set of dummies for expected project duration interacted with the expected hours required per week. Worker-level controls include cohort dummies and month dummies for the second job. Column (1) has job category dummies. The reported output is the discrete change in log wage for affiliates and non-affiliates with feedback scores of 4.5 versus feedback scores of 0. This is calculated from the agency specific constant, the coefficient on feedback, and the coefficient on the agency-feedback interaction. The regression coefficients are presented in Appendix Table 2.

Table 5: The Cross Section of Wages and Characteristics for Experienced Workers

Panel A. Summary Statistics:

	Non-Affiliates	Affiliates	Non-Affilliates	Affiliates	Non-Affilliates	Affiliates	Non-Affilliates	Affiliates
	All Job Categories		Data Entry		Web Design		Web Programming	
Log Hourly Rate	1.88	2.29**	0.72	0.42**	2.10	2.40**	2.59	2.53
	(1.00)	(0.82)	(0.65)	-1.44	(0.75)	(0.42)	(0.61)	(0.52)
Good English Skills Dummy	0.96	0.92**	0.98	0.94**	0.96	0.90**	0.93	0.92
	(0.19)	(0.27)	(0.15)	(0.25)	(0.20)	(0.30)	(0.26)	(0.27)
BA Degree or Higher	0.41	0.34**	0.46	0.34**	0.36	0.34	0.37	0.36
	(0.49)	(0.47)	(0.50)	(0.48)	(0.48)	(0.47)	(0.48)	(0.48)
Number of Total Hires	6.73	6.83	5.7	5.16	9.62	7.74**	8.16	7.37**
	(7.81)	(6.70)	(5.31)	(5.21)	(12.44)	(7.87)	(9.61)	(7.20)
Feedback Score	4.52	4.42**	4.58	4.54	4.63	4.42	4.45	4.42
	(0.68)	(0.74)	(0.66)	(0.70)	(0.74)	(0.70)	(0.73)	(0.74)
Number of Workers	5046	2446	605	93	541	419	996	1142

Panel A. Oaxaca-Blinder Decompositions of Mean Differences in Log Wages for Experienced Workers:

	All Job Categories All Countries (1)	Data Entry India and Russia (2)	Web Design India and Russia (3)	Web Programming India and Russia (4)
Data:				
Number of Affiliates	2446	27	307	780
Number of Non-Affiliates	5046	80	168	366
Mean Log Hourly Wage: Affiliates	2.293	1.146	2.384	2.541
Mean Log Hourly Wage: Non-Afiliates	1.874	0.708	2.162	2.485
Mean Difference in Log Wages	0.419	0.438	0.222	0.056
Decomposition Results:				
% Due to Agency Affiliation, Unexplained by Characteristics	17	70.2	104.9	50.4

Notes for Panel A: The sample is experienced workers with three or more total hires and non-zero feedback who are hired for their third or more job before 12/28/2009. Asterisks ** in the Affiliates column indicate that t-tests reject equality between the non-affiliates' and corresponding affiliates' values at the 5% level. Standard deviations are in parentheses.

Notes for Panel B: An observation is the first worker-month for workers who, by 12/28/2009, have had at least three hires and have non-zero feedback scores. The difference in mean monthly log wages due to agency affiliation is given by the difference in coefficients, evaluated at the mean of the affiliate characteristics. The Oaxaca-Blinder decompositions are computed using the non-affiliate "coefficients" as the base case. All columns contain a variety of controls. Continuous covariates included as controls are: the number of prior fixed price hires, revenue and feedback on prior fixed price jobs, years of pre-oDesk experience, and test scores in a variety of categories. Month dummies are included to capture differences in the market over time. Dummies are included for: reporting good English skills, reporting a BA or higher degree, reporting programming experience, missing test scores in each category, and missing experience. Column 1 contains dummy variables for each country and job category. Columns 2 through 4 restrict the sample by job category and, unlike these columns in Panel A, include only workers in India and Russia. A dummy variable for India is included in these three columns.

Table 6: Oaxaca-Blinder Decompositions of Mean Differences in First Job Outcomes

	All Job Categories All Countries (1)	Data Entry India and Russia (2)	Web Design India and Russia (3)	Web Programming India and Russia (4)
Panel A. Success Reported on First Job				
Data:				
Number of Affiliates	3717	90	264	629
Number of Non-Affiliates	7480	75	97	290
Mean Frequency of Employer Reporting Successful Project: Affiliates	0.610	0.656	0.595	0.642
Mean Frequency of Reporting Successful Project: Non-Affiliates	0.580	0.520	0.567	0.569
Mean Difference in Success Frequency between Affiliates and Non-Affiliates	0.030	0.136	0.028	0.070
Decomposition Results:				
% Due to Agency Affiliation, Unexplained by Characteristics	97.5	26.2	195.2	62.5
Panel B. Log Hours on the First Job				
Data:				
Number of Affiliates	4179	94	299	738
Number of Non-Affiliates	8614	84	114	330
Mean Log Hours on First Job: Affiliates	3.658	3.864	3.400	3.947
Mean Log Hours on First Job: Non-Affiliates	2.973	2.601	2.867	3.446
Mean Difference in Log Hours between Affiliates and Non-Affiliates	0.684	0.356	0.533	0.502
Decomposition Results:				
% Due to Agency Affiliation, Unexplained by Characteristics	53.2	71.8	81.9	100.2

Notes: An observation is a unique worker on his first hourly-paying job. The sample includes all workers whose first job application occurs between 8/1/2008 and 12/28/2009. The dependent variable in Panel A is an indicator if the employer reports the project is successful on an internal survey collected after the job ends. The dependent variable in Panel B is the log number of hours billed by the worker. Differing numbers of observations between the panels reflect jobs that are ongoing without a recorded success measure. For the linear probability model (Panel A), the decompositions are computed from the "pooled model" to account for the discrete dependent variable; Panel B uses the non-member "coefficients" as the base case. All specifications contain controls for job difficulty, including a full set of project duration and weekly expected hours interactions and the number of alpha-numeric characters in the job opening description. Worker controls are the same as in the wage decomposition. Month dummies account for differences in right-censoring propensities. Column 1 contains dummy variables for each country and job category. Columns 2 through 4 include only workers in India and Russia. A dummy variable for India is included in Columns 2-4.

Table 7: Regressions of Success on the First Job for Agency-Affiliated Workers, Across and Within Agencies

	All Jobs All Countries		Data Entry India and Russia		Web Design India and Russia		Web Programming India and Russia	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. OLS Regressions Across Agencies								
Teamwork	0.06***	0.06***	0.05	0.02	0.04	0.09	0.07**	0.07**
	(0.02)	(0.02)	(0.07)	(0.08)	(0.06)	(0.07)	(0.03)	(0.03)
Number of Prior Hires for Agency-Employer Pair		-0.00		-0.01		0.02		0.01
		(0.01)		(0.01)		(0.01)		(0.01)
Interaction of Teamwork and Prior Agency-Employer Hires		0.00		0.01		-0.02		-0.00
		(0.00)		(0.01)		(0.02)		(0.01)
Number of Workers	3717	3717	280	280	425	425	1069	1069
R-squared	0.08	0.08	0.19	0.20	0.14	0.15	0.09	0.09
Panel B. Regressions with Agency Fixed Effects								
Teamwork	0.03	0.03	-0.26*	-0.28*	0.00	0.02	0.04	0.05
	(0.02)	(0.02)	(0.14)	(0.15)	(0.11)	(0.14)	(0.05)	(0.05)
Number of Prior Hires for Agency-Employer Pair		0.00		0.00		0.04		0.01
		(0.00)		(0.03)		(0.04)		(0.01)
Interaction of Teamwork and Prior Agency-Employer Hires		-0.00		0.01		-0.02		-0.01
		(0.00)		(0.03)		(0.04)		(0.01)
Number of Workers	3717	3717	280	280	425	425	1069	1069
R-squared	0.54	0.54	0.80	0.80	0.78	0.78	0.60	0.60

Notes: Standard errors in parentheses, and *** p<0.01, ** p<0.05, * p<0.1. An observation is a unique worker on his first hourly-paying job. The sample includes all workers whose first job application occurs between 8/1/2008 and 12/28/2009. The dependent variable is from a confidential post-assignment survey that employers use to report project results to oDesk. The dependent variable is coded a 1 if the employer reports the project was completed successfully. In Panel A, regressions are across agency. Teamwork is an indicator that the worker was matched to a project with another agency worker simultaneously matched with the employer. Number of Prior Hires for Agency-Employer Pair counts the prior pairs of workers for the agency-employer pair. In Panel B, fixed effects for each agency are included. All columns contain the same controls as the original wage decomposition results given in Table 2, in addition to job opening controls that include the number of alpha-numeric characters in the vacancy announcement and dummies for expected project duration interacted with the expected hours required per week. Different observation counts due to censoring of the success measure for ongoing jobs.

Table 8: The Probability of Finding a Second Job

	All Categories (1)	Data Entry (2)	Web Design (3)	Web Programming (4)
Panel A. Estimates without first-job feedback measures				
Agency Affiliate Indicator	0.12***	0.23***	0.00	0.10**
	(0.01)	(0.03)	(0.03)	(0.03)
Observations	12794	1252	892	2206
Mean of Dependent Variable: Affiliates	0.74	0.89	0.72	0.73
Mean of Dependent Variable: Non-Affiliates	0.60	0.64	0.67	0.59
R-squared	0.15	0.15	0.15	0.15
Panel B. Estimates including first-job feedback measures				
Agency Affiliate Indicator	0.20***	0.27*	0.03	0.25***
	(0.06)	(0.08)	-0.14	(0.08)
Feedback on First Job	0.10***	0.13***	0.08***	0.13***
	(0.01)	(0.01)	(0.02)	(0.02)
Agency Affiliate x Feedback on First Job	-0.02	-0.02	-0.00	-0.04*
	(0.01)	(0.02)	(0.03)	(0.02)
R-squared	0.18	0.30	0.22	0.23
Difference in Probability of 2nd Job Between Affiliates and Non-affiliates at 4.5 Feedback Score	0.12***	0.19***	0.02	.08***

Notes: Robust standard errors clustered by country in parentheses, and *** p<0.01, ** p<0.05, * p<0.1. An observation is a unique worker on his first hourly-paying job. The sample includes all workers whose first job application occurs between 8/1/2008 and 12/28/2009. The dependent variable is a dummy variable set equal to 1 if a second hourly job is observed prior to August 14, 2010. All specifications contain controls for first-job characteristics including the number of alpha-numeric characters in the vacancy announcement and a full set of dummies for expected project duration interacted with the expected hours required per week. Worker-level controls contain cohort dummies to capture differences in transition frequency depending on when workers enter oDesk. All columns contains dummy variables for each country. Column 1 includes job-category dummies. Columns 2 through 4 restrict the sample by job category. In Panel B, the difference in probability of a second job at a 4.5 feedback score is calculated from the coefficient on the agency-affiliate indicator, 4.5 times the coefficient on feedback, and 4.5 times the (agency-affiliate x feedback) interaction. Panel C also includes other observable worker-level attributes in X_{ij} in equation (2).

Table 9: The Probability of Finding a Second Job for Agency-Affiliated Workers, Across and Within Agencies

	All Jobs All Countries (1)	All Jobs All Countries (2)	Data Entry India and Russia (3)	Data Entry India and Russia (4)	Web Design India and Russia (5)	Web Design India and Russia (6)	Web Programming India and Russia (7)	Web Programming India and Russia (8)
Panel A. OLS Regressions Across Agencies								
Teamwork	0.03**	0.04***	0.21***	0.20***	-0.03	-0.03	0.02	0.02
	(0.01)	(0.01)	(0.05)	(0.05)	(0.05)	(0.06)	(0.03)	(0.03)
Number of Prior Hires for Agency-Employer Pair		-0.00		-0.00		-0.02*		0.00
		(0.00)		(0.01)		(0.01)		(0.00)
Interaction of Teamwork and Prior Agency-Employer Hires		-0.00**		-0.00		0.01		-0.00
		(0.00)		(0.01)		(0.02)		(0.00)
Number of Workers	4179	4179	298	298	479	479	1223	1223
R-squared	0.14	0.15	0.28	0.30	0.15	0.16	0.16	0.16
Panel B. Regressions with Agency Fixed Effects								
Teamwork	-0.01	-0.00	0.08	0.09	-0.00	0.06	0.00	0.00
	(0.02)	(0.02)	(0.07)	(0.07)	(0.08)	(0.11)	(0.04)	(0.04)
Number of Prior Hires for Agency-Employer Pair		-0.00*		0.02		0.01		0.00
		(0.00)		(0.02)		(0.03)		(0.01)
Interaction of Teamwork and Prior Agency-Employer Hires		0.00		-0.01		-0.02		-0.00
		(0.00)		(0.02)		(0.03)		(0.01)
Number of Workers	4179	4179	298	298	479	479	1223	1223
R-squared	0.59	0.59	0.84	0.85	0.80	0.80	0.65	0.65

Notes: Standard errors in parentheses, and *** $p<0.01$, ** $p<0.05$, * $p<0.1$. An observation is a unique worker on his first hourly-paying job. The sample includes all workers whose first job application occurs between 8/1/2008 and 12/28/2009. The dependent variable is a dummy variable set equal to 1 if a second hourly job is observed prior to August 14, 2010. In Panel A, regressions are across agency. Teamwork is an indicator that the worker was matched to a project with another agency worker simultaneously matched with the employer. Number of Prior Hires for Agency-Employer Pair counts the prior pairs of workers for the agency-employer pair. In Panel B, fixed effects for each agency are included. All columns contain the same controls as in the original wage decomposition table, Table 2, in addition to job opening controls that include the number of alpha-numeric characters in the vacancy announcement and dummies for expected project duration interacted with the expected hours required per week.

Table 10: Conditional Logit Results, Web Programming Jobs

	All Firms	All Firms	Firms hiring Teams	Firms not hiring Teams
	Established Agencies	Well-Established Agencies		
	(1)	(2)	(3)	(4)
Constant	-2.650***	-2.630***	-2.674***	-2.669***
	(0.141)	(0.138)	(0.202)	(0.192)
Agency Affiliate	0.672***	1.389***	1.473***	1.212***
	(0.126)	(0.173)	(0.209)	(0.308)
Affiliate x Revealed Quality	-0.499**	-0.941***	-0.872**	-0.953**
	(0.198)	(0.282)	(0.353)	(0.469)
Affiliate x Revealed High Quality	-0.367***	-1.179***	-1.284***	-0.971***
	(0.135)	(0.179)	(0.216)	(0.315)
Revealed Quality	0.371***	0.328***	0.134	0.572***
(Worker has 1 prior job)	(0.110)	(0.0974)	(0.131)	(0.147)
Revealed High Quality	0.931***	0.966***	0.886***	1.081***
(Worker has 2+ prior jobs)	(0.0743)	(0.066)	(0.086)	(0.105)
Hourly Bid Rate	-0.029***	-0.029***	-0.030***	-0.027***
	(0.004)	(0.004)	(0.006)	(0.105)
Approximate Marginal Effect of Agency	0.009	0.015	0.016	0.012
Percentage Change in Choice Probability	9.9%	16.4%	17.7%	13.3%
Number of Job Openings	6376	6376	3419	2957
Observations	91653	91653	47267	44386
Log Likelihood	-10163	-10164	-5572	-4560

Notes: Robust standard errors are given in parentheses, and *** p<0.01, ** p<0.05, * p<0.1. An observation is a worker-application pair. Data include applications and wage bids for hourly job openings posted between 8/1/2008 and 11/1/2009 in Web Programming. Job openings where the employer initiates contact with workers are excluded. The dependent variable is an indicator for being hired. An outside option to not hire (normalized to 0) is included in all specifications. The constant equals 1 for all "inside" alternatives. All specifications contain a limited set of country indicators for India, the Philippines, Russia, Ukraine, and the US. Other countries are the base case. The definition of an agency in Column 1 is any agency with four or more hires. In all other columns, the definition is an agency is restricted to those agencies with 34 or more hires. Columns 3 and 4 split the sample into employers who are and who are not simultaneously employing any other workers.

Landing the First Job: The Value of Intermediaries in Online Hiring*

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APPENDIX

For Online Publication

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FOR ONLINE PUBLICATION

Appendix 1: A framework illustrating the role of agencies

This appendix presents a simple game to illustrate how agencies signal that inexperienced affiliates are high-quality—the primary agency role present in the data.[1] The model is in discrete time with an information structure similar to Tervio (2009), where worker quality is revealed on the job. In this game, there are two worker-quality levels—low and high. The equilibrium predictions from the model are robust to assuming that there is a distribution of worker qualities.[2] The following subsections describe the game and characterize a steady-state perfect Bayesian equilibrium that resembles observed outcomes in the data.

A1.1 Game Structure

There are three types of players: workers, employer firms, and an agency.[3]

Workers. Worker quality (productivity) is given by θ, which is unknown to both workers and firms when they enter the market. With probability h, a new worker is high-quality, $\theta = H$, and with probability $(1 - h)$, a new worker is low-quality, $\theta = L$, where $H > L$. Quality θ is publicly revealed after the first employment spell. An exogenous number, S, of the E arriving workers is connected to the agency. Each worker has a per-period outside option w_0, which is normalized to 0. Each worker can be employed for a maximum of two periods, and the worker's objective is to maximize lifetime earnings.

Firms. There are N identical employers (firms) that hire a single worker in each period.[4] Each employer combines labor input with other inputs to produce an output valued at the worker's quality level, θ. Firms' profits in each period are $\pi(\theta) = \theta - c - w_\theta$, where w_θ is the endogenously determined wage of the worker hired, and $c > 0$ are production costs. Long-term contracts between

[1]The findings in the data are inconsistent with a persistent agency effect on worker productivity, and cannot be explained by some of the most plausible reasons why an agency effect on worker productivity would diminish (relative to surviving non-affiliates' productivity) over a worker's career.

[2]In this case, agency affiliates are above a quality threshold, so that the distribution of worker quality among affiliates is the truncated-below quality distribution of non-affiliate workers in the data.

[3]Including only one agency mirrors the hypothesis that any one agency has a local monopoly, in that it is able to screen workers that are unconnected to any other agency.

[4]Buyer and job heterogeneity is, however, an important feature of the oDesk environment. The empirical work in Sections 3, 4 and 5 controls for observable firm and job characteristics.

firms and workers are not enforceable because workers cannot credibly commit to decline offers from other firms.

Agency. The agency owns a screening technology that can determine the quality of S inexperienced workers arriving in the market, where S is small enough that the total number of (experienced and inexperienced) agency-affiliated workers in the market in each period is less than the number of firms.[5] The agency chooses whether to offer affiliation to each screened inexperienced worker. Workers offered agency affiliation choose whether to accept the offer or to join the pool of non-affiliated new workers. Agency affiliation lasts throughout the worker's career.[6] The agency collects an endogenously determined fraction $(1 - \beta)$ of each agency affiliate's lifetime earnings, and the agency's objective is to maximize revenues.

The timing of the game in each period is as follows: (1) N firms post a single job opening. (2) E new workers, each with a per-period outside option w_0, enter the marketplace: S of these new workers are screened by the agency, which offers agency affiliation to a subset of screened workers under the revenue-sharing agreement defined by the contract β. (3) Workers offered agency affiliation choose whether to affiliate. (4) The N firms in the market hire one of: an experienced worker in the second period of his working life, known to be of either high or low quality; a new agency-affiliated worker; or a worker from the pool of inexperienced unaffiliated workers. The wages offered are: w_H, w_L, w_A, and $w_{\overline{\theta}}$, respectively. Each worker offered a job decides whether or not to accept it. The probability that an unaffiliated and inexperienced worker is employed in the first period of his life is given by p. (5) Production takes place; wages are paid to employed workers; the agency collects its revenues; and the quality of all newly-employed workers is revealed.

A1.2 A Perfect Bayesian Equilibrium

There is a perfect Bayesian equilibrium of this game where agencies offer affiliation to high-quality screened workers. Thus, agency affiliation signals to firms that inexperienced affiliated workers are

[5] S is assumed to be exogenous since the boundaries of an agency are often determined by offline networks and, hence, rely on pre-existing ties, as discussed in the introduction to the paper. Offline interaction confers the ability to screen.

[6] This corresponds to the oDesk environment. Agency affiliates leaving an agency have their personal work histories removed from their profile.

high-quality.[7,8]

Equilibrium Strategies and Beliefs

Workers. Each of the $(E-S)$ inexperienced and unscreened workers entering the market is willing to submit a wage bid below his per-period outside option w_0. Employment in the first period of workers' working lives reveals their type and, if they are high-quality, guarantees them a wage of w_H in the second period of their lives. $w_{\overline{\theta}}$ is bid down to where $p(w_{\overline{\theta}} + hw_H) = 2w_0 = 0$, so $w_{\overline{\theta}} < w_0 = 0$.[9]

Screened workers offered agency affiliation learn that they are high-quality. By offering to work at a wage of $(w_{\overline{\theta}} - \varepsilon)$ in the first period, these workers could signal to firms that they are high-quality, guaranteeing employment in both periods of their working lives and a wage of w_H in the second period. Hence, a screened worker offered affiliation has a lifetime payoff of $(w_{\overline{\theta}} - \varepsilon + w_H)$ if he does not affiliate with the agency. A firm is willing to pay w_H for an agency affiliate in each period in this equilibrium, so a worker's lifetime earnings on joining the agency are $2\beta w_H$. The agency sets β so that these workers are indifferent between affiliating and signalling their quality with a low wage bid in the first period: $2\beta w_H = w_{\overline{\theta}} - \varepsilon + w_H$. We assume that indifferent workers offered affiliation choose to affiliate with the agency.

Since the equilibrium wage for workers drawn from the pool is $w_{\overline{\theta}} < w_0 = 0$, inexperienced unscreened workers who remain unaware of their type and are not offered employment in the first period drop out of the market. They have only one more chance to be employed, and their lifetime earnings would, thus, be negative. Similarly, inexperienced screened workers who learn that they are low-quality when they are not offered agency affiliation drop out of the market. Because no screenable workers join the pool, the expected quality of a worker drawn from the pool mirrors the overall workforce, $\overline{\theta} = (1-h)L + hH$.

[7] There are three indifference conditions that hold in this equilibrium: (1) Workers unconnected to the agency are indifferent between entering oDesk and working off the platform; (2) firms are indifferent between hiring a worker known to be high-quality, hiring an inexperienced agency affiliate, and drawing from the pool of workers of unknown quality; and (3) high-quality screened workers are indifferent between affiliating with the agency and remaining independent.

[8] The variables w_H, $w_{\overline{\theta}}$, w_A, β, D, and $\overline{\theta}$ are functions of the model parameters, and the endogenous values of p and E can take any values in a bounded set. It is assumed that $H - \frac{(1-h)}{(1+h)}(H-L) > c$, $E > \frac{N-2hS}{1+h}$, and $N > h + 2hS$.

[9] In this equilibrium, wages adjust so that $w_{\overline{\theta}} + hw_H = 0$, whatever the number of workers in the pool and, hence, the probability a given worker in the pool is employed, p. This means p and, hence, E, are not determined.

Firms. Each firm believes that an affiliated worker is high-quality with probability 1, and is willing to offer the wage $w_A = w_H$ to inexperienced agency workers. If a firm ever observes a low-quality agency worker, it believes that all agency workers are high-quality with zero probability. Each of the N firms bids to employ known high-quality workers and the new agency workers. Since N exceeds the number of known high-quality workers in the market, including new affiliates, the wage for each of these workers is bid up to where firms are indifferent between hiring one of these workers at the wage w_H and drawing from the pool at the wage $w_{\overline{\theta}}$. The size of the inexperienced-worker pool is sufficiently large that $w_{\overline{\theta}}$ is bid down to where an inexperienced worker in the labor pool is indifferent between taking the job offer and remaining unemployed in the first period of his life. The firm is assumed to make non-negative profits in expectation when drawing from the pool.[10] This means that the wage of known high-quality workers, w_H, is bid up to where $\pi_H = \pi_{\overline{\theta}}$; that is, $H - c - w_H = \overline{\theta} - c - w_{\overline{\theta}}$.

Agency. The agency believes that as long as all affiliates in the past have been high-quality, then $w_A = w_H$ for each employed affiliate. The agency screens S new workers and, given that it has a sufficiently high discount rate, offers affiliation only to the hS workers who are high-quality under a contract where the agency collects $(1 - \beta)$ of affiliates' wages.

Payoffs

Workers. New agency affiliates are hired with probability 1 in each period. They receive positive lifetime payoffs equal to $2\beta w_A = 2\beta w_H$. The expected payoffs are $p(w_{\overline{\theta}} + w_H) > 0$ for a high-quality unaffiliated worker and $p(w_{\overline{\theta}} + 0) < 0$ for a low-quality unaffiliated worker.

Firms. The condition that firms are indifferent between hiring from the pool and a known high-quality worker or new affiliate, together with the zero expected lifetime payoff of unscreened workers, gives: $w_H = \frac{(1-h)}{(1+h)}(H - L)$, and $w_{\overline{\theta}} = -h\frac{(1-h)}{(1+h)}(H - L)$. That is, $w_A = w_H > w_{\overline{\theta}}$, since $H > L$; equilibrium wages are positively correlated with expected worker productivity. The expected payoff for each firm is: $\pi = H - c - \frac{(1-h)}{(1+h)}(H - L)$.

Agency. Since there are $2hS$ affiliates employed in the market, agency revenues in each period are: $R_A = 2hS(1 - \beta) w_H > 0$.[11] The agency's screening technology allows it to earn positive

[10] This assumption reflects the fact that some buyers do hire inexperienced workers in the data.

[11] Solving this gives: $R_A = 2hS(1-\beta) w_H = 2hS\left(1 - \frac{(1-h)}{2} + \epsilon\right)\left(\frac{(1-h)}{(1+h)}(H - L)\right)$, where $\epsilon = \frac{\varepsilon}{2w_H}$.

payoffs in the oDesk market.

Efficiency Implications due to the Agency

The net output in the economy in each period is total production less total fixed costs, where the production of each firm depends on the quality of the hired worker.[12] A fraction of firms employ known high-quality workers or new agency affiliates; the remaining D firms draw workers from the pool of unscreened workers. That is, the number of workers hired from the pool in each period, D, is equal to the number of firms, N, less the number of known high-quality workers remaining in the labor force from the previous period, and less the number of new agency affiliates. When $N > 2hS + hD$, D is determined by the equation $N - 2hS - hD = D$. This gives $D = \frac{N-2hS}{1+h}$. Of the draws from the pool, $(1-h)$ are expected to be low-quality. Hence, net output in each period is:

$$Y = NH - \left(\frac{1-h}{1+h}\right)(N - 2hS)(H - L) - Nc. \tag{3}$$

Setting $S = 0$ in equation (3) denotes net output in an economy with no agency. Comparative statics with respect to S provide efficiency implications. The first derivative of equation (3) with respect to S, the number of screenable workers, is positive since $h \in (0, 1)$ and $H > L$. Relative to a market outcome with no agency, the presence of an agency in this equilibrium increases allocative efficiency in the economy by reducing incomplete information about worker quality, ensuring that more jobs are taken by high-quality workers.[13]

Empirical Predictions

This equilibrium provides the theoretical motivation for the worker histories observed in the data. The first set of equilibrium predictions relates to the first job. Since employers expect that agency affiliates are higher-quality than unscreened workers on average, affiliates are predicted to receive higher initial wages than non-affiliates (shown empirically in Section 3.1). Agency affiliates' first

[12] It is assumed that there are no additional fixed costs associated with agency screening. This is reasonable in this setting since the ability to screen appears to be associated with pre-existing social connections.

[13] In the case that $H - \frac{(1-h)}{(1+h)}(H - L) < c$, the presence of the agency prevents complete market unravelling as long as $H - c > 0$. The relevant indifference condition for the firm in this case would be that $\pi_H = 0$ and, in each period, all of the $2hS$ agency members would be employed at a wage $w_A = w_H = H - c$. Hence, $(N - 2hS)$ firms would choose not to produce and no unaffiliated workers would be employed. In this case, the increase in output created by the agency presence in the market is $2hS(H - c) > 0$.

projects are also more likely to be successful (shown in Section 4.1). In addition, agency affiliates are predicted to be hired immediately, whereas non-agency affiliates experience unemployment with a non-zero probability (see Appendix 2 for this analysis).

The second set of predictions relates to outcomes on subsequent jobs. Agency affiliates are more likely to find a second job. This is because a fraction of the workers who are unscreened by the agency and do find a first job are revealed to be low-quality and are, thus, not hired a second time. Only the fraction of unscreened workers who are high-quality are hired in the second period of their lives. Since all agency affiliates are high-quality in equilibrium, all are rehired. Finally, agency affiliates are predicted to experience no wage growth, but those non-affiliated workers who are rehired experience wage growth of $(w_H - w_{\overline{\theta}}) > 0$ between their first and second job. This is due to a selection effect and an employer learning effect. The L type non-affiliates leave the market, whereas the H type non-affiliates catch up to the agency-affiliated workers in their cohort. Each of these predictions is borne out in the data, as demonstrated in Sections 3.2 and 4.2.

Appendix 2: The delay between signing up and initial hire

The data in Table 1 of the main paper show that agency affiliates are more likely to be employed for at least one job on the site. The model set out in Appendix 1, where the agency credibly signals that affiliates are high-quality, has an additional equilibrium prediction that affiliates experience less unemployment, in that they find their first job faster. This prediction is also borne out in the data.

Because job-search effort may differ by agency status, it is important to account for variation in the number of job applications and the worker's hourly wage bid over time when evaluating this prediction.[14] Each additional application is treated as a different "search" spell, and unsuccessful applications are censored. This yields a setup incorporating time-varying covariates for each worker. As in the wage analysis, specifications that limit the sample to relatively homogeneous workers in just a few job categories are included to help mitigate concerns that unobserved composition differences stemming from job categories or countries affect relative differences in delay in finding

[14] The data include a single spell of initial job search for each worker, so it is not possible to use multiple spells to control for worker-level unobserved heterogeneity. Workers have multiple jobs, but defining the start and end dates of job search after the first job proved unreliable.

work across agency affiliates and non-affiliates.

Appendix Table 7 reports hazard ratios for the whole sample and then for sub-samples of workers from Russia and India whose first bids are in Data Entry, Web Design, and Web Programming. In all specifications, the hazard ratio associated with agency affiliation is significantly greater than 1, indicating that agency-affiliated workers find their first jobs faster than unaffiliated workers.[15]

Appendix 3: Addressing potential choice set endogeneity in firms' hiring decisions

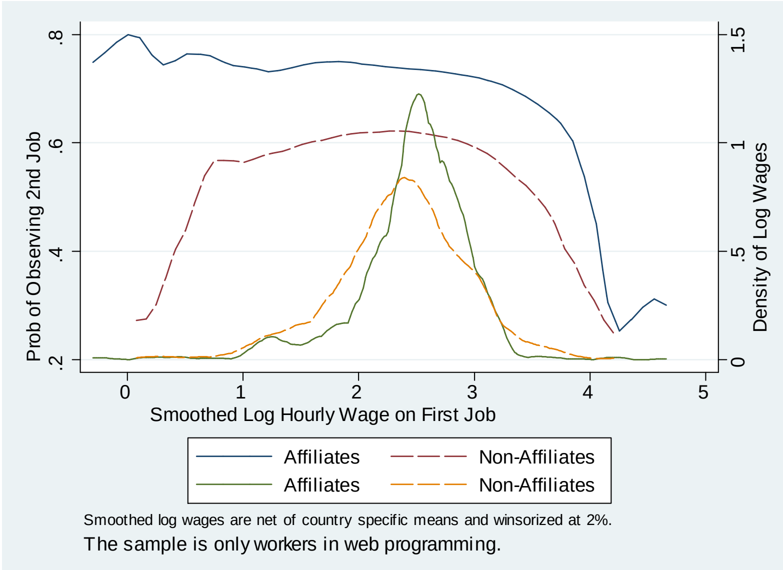
Under the hypothesis that agency affiliates are better able to distinguish, and, hence, apply to, jobs where a hire is more likely to be made, applicants (and, in particular, agency-affiliated applicants) might also be likely to tailor their behavior to employer characteristics. If workers expect that a given employer is more likely to make a hire, independent of the composition of the candidate pool, they might also be more likely to anticipate greater competition for this job posting and bid more aggressively. As would be expected, lower bid rates are associated with an increased likelihood of hiring, as previously mentioned. However, a given worker's bid rate on different jobs will be unrelated to whether a hire is eventually made if that worker is unable to anticipate which employers are more likely to hire. This hypothesis is tested by regressing hourly wages bid by all workers, and then by agency affiliates and non-affiliates separately, on an indicator variable for whether the employer eventually makes a hire. There is no significant association between bid rate and hiring outcomes for affiliates or non-affiliates, suggesting that neither group tailors its bids to unobservable firm attributes correlated with the firm's ex ante probability of hiring. These results are shown in Appendix Table 5.

Second, if workers are able to discern that some employers are more likely to hire than others, based on an unobservable attribute, workers are also, perhaps, likely to rush to apply to openings where employers are most likely to hire. This motivates an investigation of whether candidates are

[15] Alternative estimates of the relative difference in delay finding the first job confirm these results. Regressing the log number of days (plus one) elapsed between applying for the first job and being hired for the first job on an agency dummy and controls implies that agency members find their first job 26-percent faster, on average. Splitting the sample by job categories yields the largest differences for Web Programming jobs. These results are available from the authors upon request.

more likely to apply quickly to job openings if the employer ends up hiring ex-post. The unit of observation is the job opening, and the dependent variable is the number of applications for the opening within the first nine hours after it becomes visible. The results (shown in Appendix Table 6) suggest that employers who are inundated with early applications are actually less likely to hire.

Taken together, the lack of significant association between workers' actions (both affiliates and non-affiliates) and ex post employer hiring decisions supports the contention that the composition of the choice set for any one job opening is uncorrelated with the employer's ex ante propensity to hire and that the coefficient estimates in Table 10 of the paper can be interpreted as measures of the incremental employer payoffs associated with hiring workers with specific characteristics. The findings related to firm choices, therefore, offer further evidence consistent with the hypothesis that agency affiliation signals worker quality only for inexperienced workers whose quality has yet to be revealed on the job.



Appendix Figure 1: The left y-axis gives the estimated probability of survivorship as a function of the wage on the first job. The right y-axis gives the density of initial wages. Log wages on the x-axis are net of country-specific fixed effects from a first-stage regression and are winsorized at the 2% level by country.

Appendix Table 1: Summary Statistics for Workers' First Bids

Panel A. By Job Category:	Non-affiliates	Affiliates	Non-affiliates	Affiliates	Non-affiliates	Affiliates	Non-affiliates	Affiliates
	All Job Categories		Data Entry		Web Design		Web Programming	
Number of Workers Bidding	112782	12019	25757	1152	8784	1912	7041	2735
Good English Skills Indicator	0.55	0.80**	0.55	0.76**	0.46	0.77**	0.63	0.80**
BA Degree or Higher	0.23	0.30**	0.25	0.29**	0.19	0.29**	0.29	0.32**
Taken 1 or More Tests Indicator	0.48	0.42**	0.53	0.40**	0.47	0.44**	0.51	0.44**
Log Hourly First Bid	2.19	2.33**	1.78	1.55**	1.91	2.18**	2.53	2.58**
Standard Deviation of Log Bid	(0.99)	(1.01)**	(1.03)	(1.22)**	(0.99)	(0.91)**	(0.75)	(0.64)**
Panel B. By Country:	India		Russia		Philippines		US	
Number of Workers Bidding	14976	5094	1101	353	25261	1146	40597	1497
Good English Skills Indicator	0.53	0.82**	0.42	0.58**	0.57	0.73**	0.57	0.94**
BA Degree or Higher	0.26	0.30**	0.16	0.21**	0.28	0.30	0.21	0.28**
Taken 1 or More Tests Indicator	0.42	0.41	0.54	0.54	0.51	0.46**	0.49	0.41**
Log Hourly First Bid	2.01	2.23**	2.51	2.67**	1.52	1.57	2.64	3.07**
Standard Deviation of Log Bid	(0.94)	(0.77)**	(0.71)	(0.55)**	(0.97)	(1.11)**	(0.74)	(1.04)**

Notes: The sample is workers on their first hourly bid (Panel A) and first hourly hire (Panel B), including all workers whose first bid occurs between 8/1/2008 and 12/28/2009. Asterisks ** in the Affiliate column indicate that t-tests reject equality of the means for the non-affiliates' and corresponding affiliates' values at the 5% level. For the standard deviation of log hourly first bid, asterisks ** indicate that F-tests of differences in variance reject equality of variances at the 5% level.

Appendix Table 2: Wage Change between First and Second Jobs, Regression Output

These estimated coefficients are used to construct the linear combinations shown in Table 5

	All Job Categories		Data Entry		Web Design		Web Programming	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Agency Affiliate Indicator	0.051*	0.032	1.186**	1.063**	-0.054**	-0.073	-0.024	-0.043
	(0.005)	(0.006)	(0.070)	(0.076)	(0.002)	(0.019)	(0.030)	(0.041)
Feedback	0.048**	0.047**	0.183**	0.178**	0.029	0.030	0.041**	0.041*
	(0.001)	(0.001)	(0.007)	(0.007)	(0.025)	(0.024)	(0.003)	(0.004)
Affiliate * Feedback	-0.028**	-0.023**	-0.236**	-0.209**	-0.020	-0.015	-0.021	-0.017
	(0.001)	(0.001)	(0.010)	(0.011)	(0.010)	(0.006)	(0.006)	(0.008)
No Feedback Before 2nd Job Indicator	0.189*	0.186*	0.744**	0.722**	-0.025	-0.020	0.153**	0.152*
	(0.016)	(0.015)	(0.026)	(0.024)	(0.111)	(0.106)	(0.007)	(0.013)
Affiliate * No Feedback Before 2nd Job	-0.096***	-0.078**	-0.980*	-0.852*	0.081	0.099**	-0.068	-0.047
	(0.001)	(0.002)	(0.093)	(0.097)	(0.022)	(0.003)	(0.027)	(0.038)
Hours Worked Before 2nd Job	-0.000	-0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Affiliate * Hours Worked Before 2nd Job	-0.000	-0.000	-0.000	-0.000	0.000	0.001	-0.000	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Years of Prior Experience	-0.004**	-0.004**	0.005*	0.005	0.016*	0.016*	-0.009**	-0.008**
	(0.000)	(0.000)	(0.000)	(0.001)	(0.002)	(0.002)	(0.000)	(0.000)
Affiliate * Years of Prior Experience	0.006***	0.006***	-0.013*	-0.012**	-0.005	-0.005	0.013**	0.012*
	(0.000)	(0.000)	(0.001)	(0.001)	(0.008)	(0.008)	(0.001)	(0.001)
Years of Experience Not Recorded	-0.029**	-0.030**	-0.060	-0.053	0.057	0.058	-0.076**	-0.075**
	(0.002)	(0.002)	(0.036)	(0.038)	(0.019)	(0.018)	(0.002)	(0.001)
Affiliate * Years of Experience Not Recorded	0.041**	0.041**	-0.252**	-0.251**	-0.015	-0.015	0.093*	0.093*
	(0.001)	(0.001)	(0.016)	(0.020)	(0.018)	(0.018)	(0.008)	(0.009)
Difference in Agency Team Work		0.043*		0.102		0.050		0.035
		(0.006)		(0.017)		(0.024)		(0.011)
Difference in Team Work		-0.068**		-0.137**		0.001		-0.044**
		(0.001)		(0.007)		(0.007)		(0.003)
Affiliate * Difference in Team Work		0.030***		-0.118***		-0.067		0.013
		(0.000)		(0.000)		(0.017)		(0.008)
Observations	8227	8227	870	870	615	615	1463	1463
R-squared	0.050	0.053	0.127	0.138	0.123	0.126	0.075	0.079

Notes: Since the variance in log wage growth is smaller for affiliates, robust standard errors (in parentheses) are clustered by agency status, and *** p<0.01, ** p<0.05, * p<0.1. The p-values are computed using a t-distribution with a degrees-of-freedom correction because of the small number of clusters (Donald and Lang, 2007). An observation is a unique worker who has two or more hourly jobs and whose first bid occurs between 8/1/2008 and 12/28/2009. 67 observations for workers whose wages decline by more than 70% were excluded because these workers are likely paid off the platform (disintermediation).

The dependent variable is the change in log wages between jobs. All specifications contain job-opening controls (not reported), including the number of alpha-numeric characters in the vacancy announcement and a full set of dummies for expected project duration interacted with the expected hours required per week. Worker-level controls include cohort dummies and month dummies for the second job (not reported). Column 1 has job-category dummies. The effect of differences in learning or life-cycle human capital appreciation (evaluated at the mean number of hours and years of experience) is small. The results suggest that agency affiliates actually learn more on the job, implying that the effect of feedback on wage changes is not explained by differences in learning.

Appendix Table 3: Wage Change as a Function of Team Transition Types

	All Job Categories (1)	Data Entry (2)	Web Design (3)	Web Programming (4)
Agency Affiliate (Never having team work)	-0.029	0.658	-0.535**	-0.103
	(0.010)	(0.251)	(0.022)	(0.051)
Feedback	0.047**	0.185***	0.011	0.040*
	(0.001)	(0.001)	(0.023)	(0.006)
Affiliate * Feedback	-0.023**	-0.183*	0.011	-0.015
	(0.001)	(0.017)	(0.005)	(0.010)
Team to Team Transition	0.013	0.148**	-0.282***	0.031**
	(0.004)	(0.011)	(0.003)	(0.002)
Team to No Team Transition	0.089**	0.390*	-0.181**	0.040
	(0.005)	(0.060)	(0.011)	(0.013)
No Team to Team Transition	-0.047**	0.099	-0.193*	-0.047
	(0.002)	(0.039)	(0.017)	(0.008)
Affiliate * Team to Team	0.078*	0.271	0.385*	0.071***
	(0.007)	(0.131)	(0.056)	(0.001)
Affiliate * Team to No Team	0.037*	0.164	0.424**	0.085
	(0.006)	(0.182)	(0.033)	(0.024)
Affiliate * No Team to Team	0.098**	-0.052	0.287	0.117*
	(0.005)	(0.180)	(0.053)	(0.011)
Agency Team to Agency Team	-0.071	0.499	-0.537*	-0.157
	(0.014)	(0.269)	(0.063)	(0.050)
Agency Team to No Agency Team	-0.103	0.646	-0.555***	-0.190
	(0.019)	(0.213)	(0.006)	(0.073)
No Agency Team to Agency Team	-0.021	0.956	-0.447*	-0.127
	(0.008)	(0.220)	(0.036)	(0.053)
Hours Worked Before 2nd Job	-0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Affiliate * Hours Worked Before 2nd Job	0.000	-0.000	0.000	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)
Years of Prior Experience	-0.004**	0.005*	0.016*	-0.008**
	(0.000)	(0.001)	(0.001)	(0.001)
Affiliate * Years of Prior Experience	0.006***	-0.013**	-0.003	0.011**
	(0.000)	(0.000)	(0.007)	(0.000)
No Feedback Before 2nd Job Indicator	0.187**	0.747***	-0.115	0.148*
	(0.014)	(0.002)	(0.103)	(0.020)
Affiliate * No Feedback Before 2nd Job	-0.076**	-0.685	0.212***	-0.039
	(0.003)	(0.127)	(0.003)	(0.045)
Observations	8227	870	615	1463
R-squared	0.054	0.147	0.151	0.083

Notes: Robust standard errors clustered by agency status in parentheses, and *** p<0.01, ** p<0.05, * p<0.1. Note that p-values are non-standard because of the small number of clusters. An observation is a unique worker who has two or more hourly jobs, among those workers whose first hire occurs between 8/1/2008 and 12/28/2009. 67 observations for workers whose wages decline by more than 70% were excluded because these workers are likely paid off the platform (disintermediation). The dependent variable is the change in log wages between jobs. Transitions indicate whether the whether the first job was team-based or not, whether the second job was team-based, and allow the effect to differ by agency affiliation.

Appendix Table 4: The Probability of Finding a Second Job as a Function of Initial Characteristics

	All Categories		Data Entry		Web Design		Web Programming	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Main Effects								
Log Hourly Wage	-0.02***	-0.02***	-0.00	-0.01	-0.02	-0.02	-0.00	-0.01
	(0.01)	(0.01)	(0.02)	(0.01)	(0.03)	(0.03)	(0.02)	(0.02)
Feedback		0.10***		0.13***		0.08***		0.13***
		(0.01)		(0.01)		(0.02)		(0.02)
No Feedback Before 2nd Job Indicator		0.40***		0.57***		0.33***		0.45***
		(0.03)		(0.03)		(0.10)		(0.09)
Good English Skills Dummy	0.21***	0.21***	0.16***	0.14***	0.19*	0.20**	0.14***	0.14***
	(0.02)	(0.02)	(0.04)	(0.04)	(0.10)	(0.10)	(0.04)	(0.04)
BA Degree or Higher	-0.00	-0.00	0.04**	0.03	0.05	0.03	0.02	0.01
	(0.02)	(0.01)	(0.02)	(0.02)	(0.05)	(0.05)	(0.04)	(0.04)
Pre oDesk Years Experience	-0.00	-0.00	-0.00	-0.00	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
Agency Affiliate Interactions								
Agency Affiliate Dummy	0.23***	0.00	-0.04	-0.05	-0.03	0.00	0.63***	0.72***
	(0.05)	(0.00)	(0.07)	(0.08)	(0.26)	(0.00)	(0.17)	(0.18)
Log Hourly Wage	-0.03***	-0.03***	0.00	-0.01	0.02	0.00	-0.04	-0.04
	(0.01)	(0.01)	(0.03)	(0.03)	(0.06)	(0.05)	(0.03)	(0.03)
Feedback		-0.02*		-0.02*		-0.01		-0.04**
		(0.01)		(0.01)		(0.03)		(0.02)
No Feedback Before 2nd Job Indicator		-0.09**		0.00		-0.09		-0.13
		(0.05)		(0.05)		(0.11)		(0.10)
Good English Skills Dummy	-0.03	-0.03	-0.03	-0.02	0.01	0.01	-0.01	-0.01
	(0.03)	(0.03)	(0.06)	(0.08)	(0.14)	(0.14)	(0.03)	(0.03)
BA Degree or Higher	-0.01	-0.01	-0.03	-0.02	-0.05	-0.01	0.04	0.05
	(0.04)	(0.02)	(0.05)	(0.05)	(0.06)	(0.06)	(0.06)	(0.06)
Pre oDesk Years Experience	0.00	0.00	0.02***	0.02***	-0.01	-0.01	-0.01	-0.01
	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Observations	12794	12794	1252	1252	892	892	2206	2206
R-squared	0.15	0.18	0.26	0.31	0.22	0.25	0.20	0.24

Notes: Robust standard errors clustered by country in parentheses, and *** p<0.01, ** p<0.05, * p<0.1. An observation is a unique worker on the first hourly hire, including all workers whose first hire occurs between 8/1/2008 and 12/28/2009. The dependent variable is a dummy variable set equal to 1 if a second hourly job is observed prior to August 14, 2010. All specifications contain country fixed effects, monthly cohort dummies, test scores, the number of fixed-price hires, and (job duration x hours per week) dummies. All specifications contain main effects and agency interactions for all right-hand-side variables except country fixed effects, cohort, and job category fixed effects (not reported). Other main effects and interations that are not reported are insignificant.

Appendix Table 5: Log Wage Regressions Measuring Strategic Bidding in Web Programming

	Pooled		Agency Members		Non-Members	
	(1)	(2)	(3)	(4)	(5)	(6)
Employer Makes a Hire	-0.00*	-0.00	-0.00	-0.00	-0.00	-0.00
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Experienced Buyer	-0.01***	-0.01***	-0.00*	-0.00	-0.01***	-0.01***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Open Description Length	0.00	-0.00	-0.00	-0.00	0.00	-0.00
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Experienced Buyer x Description Length	-0.00	0.00	0.00	0.00	-0.00	0.00
	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)
Observations	85155	85145	18128	18128	67017	67017
R-squared	0.816	0.916	0.830	0.933	0.816	0.914

Notes: Robust standard errors clustered at the country level in parentheses, and *** p<0.01, ** p<0.05, * p<0.1. An observation is a worker-bid pair. Data include bids for hourly job openings posted between 8/1/2008 and 11/1/2009 in Web Programming. Job openings where the employer initiates contact with workers are excluded. Columns 1, 3, and 5 contain (year x week) and worker fixed effects. Columns 2, 4, and 6 contain (year x month x worker) fixed effects.

Appendix Table 6: Candidacy Arrival Rates Measuring Strategic Job Applications in Web Programming

	All Applications (1)	Agency Affiliate Applications (2)	Non-Affiliate Applications (3)
Eventually Hires	-3.490***	-1.369***	-2.121***
	(0.532)	(0.222)	(0.356)
Job opening has a detailed description	-0.577	0.0305	-0.608**
	(0.430)	(0.180)	(0.288)
Eventually hires x detailed description	0.730	0.179	0.550
	(0.720)	(0.300)	(0.482)
Observations	3990	3990	3990
R-squared	0.040	0.031	0.036

Note: Standard errors in parentheses, and *** p<0.01, ** p<0.05, * p<0.1. The dependent variable is the arrival rate of bids over the first nine hours after a job opening is posted in Web Programming. The sample for this analysis comes from late Fall 2009 and is a subset of the sample used in the conditional logit analysis reported in Table 10. This sample was used because of some inconsistently recorded application times in the larger sample. A detailed job-opening description is one that has more than the median number of alpha-numeric characters.

Appendix Table 7: Cox Proportional Hazard Results of Time to First Hire

	Three Main Job Categories All Countries	Data Entry India and Russia Only	Web Design India and Russia Only	Web Programming India and Russia Only
	(1)	(2)	(3)	(4)
Log Hourly Rate	0.53***	0.62***	0.62***	0.63***
	(0.01)	(0.02)	(0.02)	(0.02)
Agency-Affiliate Indicator	1.30***	1.47***	1.49***	1.44***
	(0.06)	(0.10)	(0.10)	(0.09)
Bid Number	1.01***	1.01***	1.01***	1.01***
	(0.00)	(0.00)	(0.00)	(0.00)
Number of Fixed-Price Hires	1.24***	1.29***	1.29***	1.29***
	(0.01)	(0.03)	(0.03)	(0.03)
Worker is from India		0.69	0.84	0.24***
		(0.69)	(0.25)	(0.03)
Observations	368071	128635	129436	131045

Notes: z-statistics in parentheses, and *** p<0.01, ** p<0.05, * p<0.1. An observation is a unique worker on the first hourly hire, including all workers whose first bid occurs between 8/1/2008 and 12/28/2009. All columns include skill and experience controls similar to the Oaxaca-Blinder specifications. Column 1 includes country and job category indicators.